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Modelling artificial intelligence in economics

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Abstract

We provide a partial equilibrium model wherein AI provides abilities combined with human skills to provide an aggregate intermediate service good. We use the model to find that the extent of automation through AI will be greater if (a) the economy is relatively abundant in sophisticated programs and machine abilities compared to human skills; (b) the economy hosts a relatively large number of AI-providing firms and experts; and (c) the task-specific productivity of AI services is relatively high compared to the task-specific productivity of general labor and labor skills. We also illustrate that the contribution of AI to aggregate productive labor service depends not only on the amount of AI services available but on the endogenous number of automated tasks, the relative productivity of standard and IT-related labor, and the substitutability of tasks. These determinants also affect the income distribution between the two kinds of labor. We derive several empirical implications and identify possible future extensions.

Keywords: Artificial intelligence, Automation, Labor economics, Mathematical models

JEL Classification: O47, O33, J24, E21, E25

1 Introduction

Until recently, there was relatively little research in economics on artificial intelligence (Agrawal et al. 2019). This situation is rapidly changing, however. Most progress so far has been on understanding the potential labor market implications of AI, in particular using the task-approach to labor markets (e.g., Autor (2013)). This approach has been used amongst others to evaluate fears that AI-automated job losses would cause mass unemployment.[1]

Acemoglu and Restrepo (2018) incorporated the task-approach into an endogenous growth model, making further progress in modelling AI in economics. The Acemoglu-Restrepo (AR) model is a general automation-technology model - with AI being one of several automation technologies that can be used to analyse. Other automation technologies include robots, as for instance discussed in Acemoglu and Restrepo (2017) and Chiacchio et al. (2018).

The AR-model thus does not focus on AI specifically. It also considers tasks and skills in automation, but not abilities. Abilities may, as several scholars recently argued, better characterize the nature of the services that AI provides (Hernández-Orallo 2017; Tolan et al. 2020). The contribution of this paper is to propose a partial equilibrium model wherein AI provides abilities that are combined with human skills to provide an aggregate intermediate service good. While our mathematical formulation (see section 3) makes explicitly clear what we mean by the difference between skills and abilities where AI is concerned, it is perhaps helpful that we also provide, at the outset, an intuitive explanation.

Consider for instance that the visual recognition of objects is an *ability*—the ability to see—and that this

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[1] Fears of AI-automated job losses were prompted by estimates of Frey and Osborne (2013) (also in Frey and Osborne (2017)) that 47 percent of jobs in the USA could be automated in 10 to 20 years. Subsequent analyses have been critical of this work because it mixed up the technological feasibility of automation with potential employment effects and because it exaggerated the technological feasibility of automation (Arntz et al. 2016). Arntz et al. (2017) used different assumptions and estimated that only 9 percent of OECD jobs were possibly subject to automation. Furthermore, Autor (2015) has argued that apocalyptic job losses are unlikely, because automation tends to affect tasks, rather than entire jobs.

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ability can be used to perform a *task*, for instance the task of driving a car, or the task of recognizing faces. Applying the ability of being able to see to either driving, or facial recognition, require *skills*, which requires human judgement. Thus, even though an AI model can drive a car because of its ability to "see" we still need human skills to make the decision and judgement to apply the ability to the task of driving. No AI algorithms (yet) autonomously decide where and how to apply various abilities, which in the case of current AI, predominantly Machine Learning (ML), is based on big data. It is this combination of human skills, particularly ICT skills, that in combination with AI's big-data-based abilities results in AI applications. In the model we present here, we provide a detailed description of this combination of AI abilities, data, and human ICT skills in our production function.

The purpose of this paper is therefore to complement the task-approach and AR-model. By combining AI abilities with human skills to provide an aggregate intermediate service good, we can determine the efficient allocation of AI and labor in production in a manner that is comparable to the traditional notion of labor in efficiency units. The main take-away is that the extent of automation through AI technologies will be greater if (i) the economy is relatively abundant in sophisticated programs and machine abilities compared to human skills; (ii) the economy hosts a relatively large number of AI-providing businesses and experts; and (iii) the task-specific productivity of AI services is relatively high compared to the task-specific productivity of general labor and labor skills. Our model can be imported as a package into general equilibrium endogenous growth models to elaborate the economy-wide effects of AI—thus expanding the toolkit of economists.

The paper will proceed as follows. In Sect. 2, we describe our background with reference to the basic mathematical set-up of the task-approach to labor markets, as well as by setting out the core of the AR model's incorporation of the task-approach into an endogenous growth setting. This indicates that our model remains close to the spirit of the task-approach and the AR-model. In Sect. 3 we present our model. Section 4 contains a discussion of the results and implications of the model, while Sect. 5 concludes with a summary and indication of potential extensions.

2 Background

This paper's overall contribution is to present a novel theoretical approach to the way that Artificial Intelligence (AI) is incorporated into economic models in a way that complements existing frameworks for studying automation, such as the task-approach and AR-model. Since AI is expected to become a driver of productivity and automation, the interaction of labor and AI and its effects on the aggregate economy are of particular interest. Thus, we need a suitable tool of modeling that can be easily imported into other models like growth or dynamic labour market theories. In order to facilitate understanding of our method, and appreciation of our results as described in section 3, we set out in the remainder of this section to present the core of the task-approach in terms of its use to study automation, as well as the core of the AR growth model, given that our model remain close in spirit and approach to these two contributions.

The main conceptual approaches used by economists to investigate the labor market impacts of automation have been the task-approach to labor economics, see e.g. Acemoglu and Autor (2011) and and Autor and Dorn (2013) and the Acemoglu-Restrepo Growth (AR-Model), see Acemoglu and Restrepo (2018). Because the AR-model incorporates the task-approach we can start with its central equation, a production function (see p.1494), where β is a constant and $y(i)$ a unit measure of tasks[2]:

$$Y = \beta \left[\int_{N-1}^{N} y(i)^{\frac{\eta-1}{\eta}} di \right]^{\frac{\eta}{\eta-1}} \tag{1}$$

Acemoglu and Restrepo (2018) furthermore specify separate production functions for tasks that can be automated, and for tasks that cannot be automated but provided only with labor. This follows from their indexing tasks ranging from $N-1$ to N so that there can be a point $I \in [N-1, N]$ with tasks $i \leq I$ that can be automated, and tasks $i > I$ that cannot be automated - the assumption is that labor has a comparative advantage in tasks high up in the index. For tasks $i > I$ they specify the following CES production function (p. 1494):

$$y(i) = \beta(\zeta) \left[\eta^{\frac{1}{\zeta}} q(i)^{\frac{\zeta-1}{\zeta}} + (1-\eta)^{\frac{1}{\zeta}} (\gamma(i) l(i))^{\frac{\zeta-1}{\zeta}} \right]^{\frac{\zeta}{\zeta-1}} \tag{2}$$

And for tasks $i \leq I$ a similar specification is used, except with the inclusion now of capital (k), which is a perfect substitute for labor l with CES elasticity $\eta \in (0, 1)$:

$$y(i) = \beta(\zeta) \left[\eta^{\frac{1}{\zeta}} q(i)^{\frac{\zeta-1}{\zeta}} + (1-\eta)^{\frac{1}{\zeta}} (k(i) + \gamma(i) l(i))^{\frac{\zeta-1}{\zeta}} \right]^{\frac{\zeta}{\zeta-1}} \tag{3}$$

where $\gamma(i)$ is the productivity of labor in task i, $\zeta \in (0, \infty)$ the elasticity of substitution between intermediate inputs (q) and labor inputs (l).

Where is artificial intelligence (AI) in this model?

[2] A task is "a unit of work activity that produces output"(Autor et al. 2003, p. 186).

AI is not explicitly modelled (nor defined); rather, it is firstly contained in q[3], which the authors define as "a task-specific intermediate [...] which embodies the technology used either for automation or for production with labor." Furthermore, technological progress (e.g. progress in AI) is of two kinds: it can either make more tasks amendable to automation (reflected in a shift of I) or transform old tasks that could be automated into new tasks in which labor has a comparative advantage, reflected in an increase in $N-I$ and a reduction in $I-(N-1)$. In a static version of the AR-model, k is fixed and technology (including AI) exogenous. As such, technological innovation changes the allocation of tasks between capital and labor, and this in turn will change relative factor prices—with consequences for employment and the wage share of labor.

With these production functions for tasks carried over into a dynamic setting, Acemoglu and Restrepo (2018) endogenize capital and technological progress, and tease out the long-run implications of automation on jobs and inequality. Now, the price of capital relative to the wage rate will determine the extent to which new tasks are created, and they show that a stable balanced growth path is possible if progress in automation and creation of new tasks are equal. Any deviations from this will set corrective market forces in operation. In other words, automation has reinstatement effects (creation of new tasks)[4]. As they put it "This stability result highlights a crucial new force: a wave of automation pushes down the effective cost of producing with labor, discouraging further efforts to automate additional tasks and encouraging the creation of new tasks"(Acemoglu and Restrepo 2018, p. 1491).

3 Method and results: modelling AI in production

As the method section above outlined, the task-approach to labor markets and the AR-model offer important and useful contributions to model automation technologies in economics. These are general approaches that provides insights into all automation technologies, from robots to AI. While being general has its advantages, the disadvantage is that the specific features are omitted. In the case of AI, these specific features may however matter, for example for extent to which it diffuses in the economy. Unlike most other automation technologies, AI depends on big data, a resource that tends to be non-rival in use, and high levels of human ICT skills. In this section, we propose a partial equilibrium model wherein we incorporate these specific features of AI.

3.1 Human service as intermediate good

If AI is essentially a technology that provides specific abilities, it will always need to be combined or used in tandem with skills, which are, as we pointed out above, distinct human attributes requiring experience, knowledge and common sense (Tolan et al. 2020). We define this combination of AI and human skills as *human services*, H. To be precise, a human service is an intermediate service good that is generated by variously skilled human labor and AI. Human service $[H=H(Labor, AI)]$ is produced following the task-approach to labor markets specification; however, it can be easily included in any conventional production function leading to a nested production process $Y=Y(H,K)$. Due to this nested structure, the *human service task-approach* that we propose here allows us to analyze and separately discuss effects specific to the task-approach, without much increase in model complexity. Thus, a shortcoming of the AR modeling—its high complexity—is (somewhat) addressed.

The human service production function can be written as $H=H(L_L, A_L, A_{IT}, B_{IT})$. Here L_L is the number of workers each providing given hours of work, A_L is an index of human skills (reflecting experience and human abilities), A_{IT} is the total number of ML abilities (e.g. algorithms) in the economy and B_{IT} are the IT-business owners or experts providing and running AI services. Hence, our approach enriches and extends the simple task-approach by integrating human skills with AI abilities, as per the arguments of Hernández-Orallo (2017) and Tolan et al. (2020).

The production function for human services can be specified as (note the similarities as well as the differences with (3) and (4) and (5)):

$$H=\left(\int_{N-1}^{N} h(z)^{\frac{\sigma-1}{\sigma}}dz\right)^{\frac{\sigma}{\sigma-1}} \tag{4}$$

where z denotes each task in a unit interval $[N-1,N]$, and $h(z)$ is the output of task z. As tasks range between $N-1$ and N, the total number of tasks is constant, and σ is the elasticity of substitution. Note that whereas Acemoglu and Restrepo (2018) define total production as result of $N-1$ to N tasks, we propose to define total production as the result of human service inputs and other inputs like capital or other intermediates, where human service inputs consist of the outputs of different tasks. Further, with L_L and B_{IT} we separate between labor and

[3] Our contribution in this paper essentially consists of elaborating this q term in the AR-model's production function—see section 3.1.

[4] While the AR-model highlights that there exists a long-term balanced growth path it also allows for short and medium run deviations. For instance, Acemoglu and Restrepo (2019) show that current developments on the US labor market can be explained by an acceleration of automation and a deceleration of reinstatement effects.

owners, respectively providers of AI as a more or less disembodied technology.

Each task z can either be produced with labor, $l(z)$, or only with AI services provided by AI-businesses, $b_{IT}(z)$, if the task can be done by AI. Therefore, there are two sets of tasks. Tasks $z \in [N-1, N_{IT}]$ can be produced by both labor and AI services [described by process (a) in (5)], and tasks $z \in (N_{IT}, N]$ can onlybe produced by labor [process (b) in (5)]. These tasks can be the niche in which labor can continue to specialize in the presence of AI driven services or automation, as per Arntz et al. (2017). Thus, the output of a task can be stated in two ways

$$h(z) = \begin{cases} \gamma_L(z)l(z)A_L + \gamma_{IT}(z)b_{IT}(z)A_{IT}D & \text{process (a) if } z \in [N-1, N_{IT}] \\ \gamma_L(z)l(z)A_L & \text{process (b) if } z \in (N_{IT}, N] \end{cases} \tag{5}$$

Note that the production process (a) implies perfect substitution of human labor abilities by AI, as the human labor ability ($A_L\gamma_L(z)l(z)$) is not a necessary input for this task. To provide further justification for the specification in (5) we can note the following:

First, while $l(z)$ is the volume of hours employed in the specific task z , A_L is a description of generally available skills, which includes human *abilities* and *experiences.* So humans who are employed, irrespective of which tasks they perform, are endowed with A_L. Humans can identify problems, understand social signals and social interactions, detect and handle positive and negative social externalities in groups, can use common sense, and can think ahead. These very human skills have emerged over hundreds of thousands of years of biological evolution interacting with the environment and culture, including education. As these human skills indexed by A_L are homogeneously related to all human labor L_L this endowment is potentially available in each task z without rivalry and similar to a public good, $A_Ll(z)$. However, in some tasks these human skills are particular valuable while in others, they are not really needed. This task specific productivity is indicated by $\gamma_L(z)$. Thus, in (5) total human contribution to a task is $\gamma_L(z)A_Ll(z)$.

Second, as far as production with AI is concerned, A_{IT} denotes the total number and quality of ML algorithms or *machine abilities* in the economy that can provide a general AI service. The idea here is that an AI service contains two components. One is a general AI algorithm or code and the other is a specific application of the algorithm based on particular data. For example, A_{IT} would include various generic Machine Learning (ML) models and techniques, from logistical regressions to Deep Learning (DL) and Convolutional Neural Networks(CNN). These algorithms are nonspecific with respect to a particular domain of usage. As such, they can be used without rivalry, and to the extent that they may be excludable through licensing may have the characteristics of a club good.

Since ML algorithms are trained on data (training can be either supervised or unsupervised by a skilled human), data D is the raw material needed to produce an AI service. Hence, we can denote the complementarity between data and algorithms as $A_{IT}D$, which is the fundamental infrastructure for specific AI services. Since the use of data is non-rival, $A_{IT}D$ is a club good. Note, however, that $A_{IT}D$ is yet not an AI service. The AI service is obtained when $A_{IT}D$ is applied to a particular task—where it creates value. This application is facilitated by IT experts $b_{IT}(z)$ who tailor $A_{IT}D$ for a particular purpose or business opportunity, z, adding up in total to B_{IT} applications.

It is perhaps useful here to highlight the essential difference between AI as automation technology and other automation technologies, such as robots. Like AI, robots also have abilities. These abilities, like that of say capital equipment, is for example to have much greater strength and endurance than humans. Humans use their skills to apply robotic strength and endurance where it can add economic value. Robots do not decide this themselves. In this, they are thus similar to AI. Where they are different from AI is in the complimentary skills that their deployment require. AI, as opposed to robots are data and ML (algorithm/software) intense, and this has, as we show below, slightly different implications for the extent of automation.

Finally, AI services that have been tailored to a particular task will be characterised by different levels of task-specific productivity, $\gamma_{IT}(z)$. In total, therefore, AI services production for a particular task z can be described as $\gamma_{IT}(z)b_{IT}(z)A_{IT}D$ in (5a).

3.2 AI abilities and the demand for tasks

If a task z with price $p_h(z)$ is produced with standard labor $h(z) = A_L\gamma_L(z)l(z)$, and labor rewards are calculated according to marginal productivity, then $p_h(z)A_L\gamma_L(z) = w_L$. Symmetrically, the same task could be produced with AI technology so that $p_h(z)A_{IT}\gamma_{IT}(z) = w_{IT}$, with w_{IT} as the reward for the AI supplying expert or business. Given these two conditions, and given wages in the market, for any particular task the firm will choose the kind of service composition (AI service/automation or not) that results in the lowest unit labor costs. Thus, if the following condition holds, the task will be provided by the AI service:

$$\frac{w_{IT}}{p_h(z)A_{IT}\gamma_{IT}(z)} < \frac{w_L}{p_h(z)A_L\gamma_L(z)}$$

This rule leads to condition (6) which identifies the switching point between automated (AI) tasks and labor tasks. If tasks are ordered in such a way that $\frac{A_L\gamma_L(z)}{A_{IT}\gamma_{IT}(z)}$ is increasing in z and the tasks with lower numbers $z \in [N-1, N_{IT}]$ are the automated tasks, task N_{IT} is the switching point from an automation task to a labor task. N_{IT} is the highest number in this order for which

$$\frac{A_L\gamma_L(N_{IT})}{A_{IT}\gamma_{IT}(N_{IT})} < \frac{w_L}{w_{IT}} \tag{6}$$

holds. Apart from these automated (AI) tasks $[N-1, N_{IT}]$, all other tasks $(N_{IT}, N]$ are produced with standard labor. Thus, the costs and respectively the price $p_h(z)$ for any task z is

$$p_h(z) = \begin{cases} \frac{w_{IT}}{A_{IT}\gamma_{IT}(z)} & \text{if } z \in [N-1, N_{IT}] \\ \frac{w_L}{A_L\gamma_L(z)} & \text{if } z \in (N_{IT}, N] \end{cases} \tag{7}$$

We can use this to calculate the endogenous optimal number of *tasks provided by AI* in an economy with an efficient supply of the human service:[5]

$$N_{IT} = N_{IT}(B_{IT}, L_L, A_{IT}, ...), \text{ with } \frac{dN_{IT}}{dB_{IT}} > 0, \quad \frac{dN_{IT}}{dL_L} < 0, \quad \frac{dN_{IT}}{dA_L} < 0, \quad \frac{dN_{IT}}{dA_{IT}} > 0 \tag{8}$$

This result indicates that the number of automated/machine produced tasks crucially depends on the relative availability of various input factors. The extent of implementation and diffusion of AI technologies and automation of human services will depend on the relative availability of the specific inputs of the human service. It is thus not only the availability of AI technologies (A_{IT}) that matters, but also the availability of AI experts who are able to use and run this technology (B_{IT}) as well as the productivity (A_L) and amount of standard labor (L_L).

3.3 Optimal human service supply

Why are we interested in the total supply of the human service? In many models, in particular growth models, capital can be accumulated with ease, and labor is the limiting factor of production. This leads to the concept of labor in efficiency units, which can be simply expressed as a multiplication of the amount of physical labor with a technology index. Human service supply is obtained with a task-production mechanism that combines the two kinds of labor into total productive service of available labor. As we will see, it is a rather complex way for technological innovation to affect the aggregate productive labor service (9) and the distribution of productivity and labor income (see next Sect. 3.4).

From the demands for the various tasks derived in the previous subsection, total human service production can be derived. Aggregating automated tasks and labor, Eq. (4) leads to

$$H = \left(\int_{N-1}^{N_{IT}} h(z)^{\frac{\sigma-1}{\sigma}} dz + \int_{N_{IT}}^{N} h(z)^{\frac{\sigma-1}{\sigma}} dz \right)^{\frac{\sigma}{\sigma-1}}.$$

Using (12), (17) and 18), respectively, and re-arranging gives the expression for total production of human services as:[6]

$$H = \left(\left(\int_{N-1}^{N_{IT}} \gamma_{IT}(z)^{\sigma-1} dz \right)^{\frac{1}{\sigma}} (A_{IT}B_{IT})^{\frac{\sigma-1}{\sigma}} + \left(\int_{N_{IT}}^{N} \gamma_L(z)^{\sigma-1} dz \right)^{\frac{1}{\sigma}} (A_L L_L)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$$

With the definitions $\Gamma_{IT}(N_{IT}, N) = \int_{N-1}^{N_{IT}} \gamma_{IT}(z)^{\sigma-1} dz$ and $\Gamma_L(N_{IT}, N) = \int_{N_{IT}}^{N} \gamma_L(z)^{\sigma-1} dz = \Gamma(N_{IT}, N)\Pi(N_{IT}, N)^{\sigma-1}$ we can rewrite the aggregate optimal human service production as

$$H = \left[(\Gamma_{IT}(N_{IT}, N))^{\frac{1}{\sigma}} (A_{IT}B_{IT})^{\frac{\sigma-1}{\sigma}} + \Gamma_L(N_{IT}, N)^{\frac{1}{\sigma}} (A_L L_L)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}. \tag{9}$$

This expression is similar to the familiar Constant Elasticity of Supply (CES) production function. Thus, the two kinds of labor combine in a complex way to an aggregate productive service. To what extent a particular technology contributes to the aggregate productive service not only depends on the specific technology, but also on the endogenous number of tasks provided by AI services (N_{IT}), the (over the tasks) aggregated productivity of each kind of labor (Γ_{IT}, Γ_L) and the elasticity of substitution σ.

[5] See the Appendix.

[6] For details see Appendix.

3.4 Distributional effects

From (9) we learn that the total productive human service decomposes into two services from standard labor and IT related labor. Thus, we can derive the income share for this service of each kind of human labour inputs. As we show in Appendix, an increase in the availability of AI (A_{IT}) will decrease the standard labor share of income if the elasticity of substitution (σ) is sufficiently high (σ does not even need to be larger than one).

$$\eta_{\phi_L,A_{IT}} = \frac{d\phi_L}{dA_{IT}}\frac{A_{IT}}{\phi_L} = \frac{-1}{\sigma}\frac{(\sigma-1)+\left(\frac{\gamma_{IT}(N_{IT})^{\sigma-1}}{\Gamma_{IT}(N_{IT},N)}+\frac{\gamma_L(N_{IT})^{\sigma-1}}{\Gamma_L(N_{IT},N)}\right)N_{IT}\eta_{N_{IT},A_{IT}}}{1+\left(\frac{A_L L_L}{A_{IT}B_{IT}}\right)^{\frac{\sigma-1}{\sigma}}\left(\frac{\Gamma_L(N_{IT},N)}{\Gamma_{IT}(N_{IT},N)}\right)^{\frac{1}{\sigma}}} < 0. \tag{10}$$

Then, the AI service can easily substitute for the tasks of standard labor. This means that there is a distributional effect from a large availability of AI on cost of standard labor. The final outcome will however also depend on other parameters. In particular we have to consider the relative availability of *human skills* to *machine abilities* A_L/A_{IT}; the relative abundance of the volume of *labor* to *AI-supplying experts* L_L/B_{IT}; the relative task-specific productivity at the switch point $\gamma_L(N_{IT})/\gamma_{IT}(N_{IT})$; and the volume and veracity of data available to run all these AI services, D. Thus, our modelling of AI provides a level of detail of specification that is lacking in the AR-model.

4 Discussion

The task-approach to labor markets and the AR-model offer important and useful contributions to model automation technologies in economics. They are general approaches that provide insights into all automation technologies, from robots to AI. While being general has its advantages, the disadvantage is that the specific features of the technology is omitted. The specific features may matter—in the case of AI we have argued that unlike other automation technologies most frequently considered in economics, such as robots,[7] AI offers different or specific abilities, (rather than skills), which can only be applied based on data and human ICT skills.

Several scholars have argued that abilities better characterizes the nature of the services that AI provide (Hernández-Orallo 2017). According to Tolan et al. (2020, p. 6–7) abilities are "a better parameter to evaluate progress in AI"because ML provide abilities to do tasks, and not skills, which are human attributes requiring experience, knowledge, and common sense. Skills are not an attribute of AI. This means that, with AI providing abilities, such as the ability to understand human language or recognize objects, it is necessary to go beyond skills and tasks when evaluating any labor market impacts of AI, because the adoption of AI will ultimately depend on its abilities *relative* to the abilities of human labor.

Some abilities may be more (or less) likely to be provided by AI, which means that "AI may cause workplaces to transform the way a task is performed" (Tolan et al. 2020, p. 6). In other words, the technological feasibility of AI in automation will depend on the extent that it changes the very nature of tasks. This however cannot be modelled adequately by the task approach to labor markets and its incorporation into the AR-model. The mechanism that we proposed in section 3 of this paper, wherein we modelled AI in production as providing abilities, in line with the recent contribution of Tolan et al. (2020), is thus a contribution to address this shortcoming. It can be combined in various models in economics, from labor market to endogenous growth models. It is also relevant for industrial economics models given the characteristics of data and ML programs as public or club goods.

5 Conclusion

In this paper, we contributed to the modeling of Artificial Intelligence (AI) in economics by building on the task-approach to labor markets to reflect the distinctiveness of AI not as a task or skill, but as an ability. Our ability-sensitive specification of the task-approach allowed us to gain further insights into the labor market consequences of AI progress. The main take-away from our model is that an economy will broadly (large N_{IT}) utilize AI technologies if (i) the economy is relatively abundant in sophisticated programs and machine abilities compared to human skills; (ii) the economy hosts a relatively large number of AI-providing businesses and experts; and (iii) the task-specific productivity of AI services are relatively high compared to the task-specific productivity of general labor and labor skills. Further, as access to data—a resource characterised by non-rival use, is essential for task-specific AI in our model, its relative abundance will be an essential determinant of the diffusion—and hence impact—of AI.

Our model has two broad empirical implications. The first relates to the difference between abilities and tasks. Making this distinction has generated empirically testable predictions regarding the extent of automation and

[7] Robots do indeed have abilities! For the difference with AI, see the discussion in section 3.1.

ICT skills. If, for instance, IT experts or business solutions are widely available, more tasks will be automated. Similarly, if IT knowledge and AI algorithms are readily available, relative wages $\frac{w_L}{w_{IT}}$ will increase, and human labor tasks will become relatively more expensive, furthering automation. Second, by embedding our model in a growth model (as in Gries and Naudé (2021)) the income distribution consequences of automation can be more finely delineated, as the model allows for distinct treatment of data and algorithms, IT experts and non-expert human labor on the other, and their different ownership structures. From such a delineation, various testable empirical implications may emanate, for instance such as that AI progress can occur at the same time as stagnation (Gries and Naudé 2021).

Finally, there is scope for refinement of our model. For instance, one empirical implication is that if IT knowledge and AI algorithms are readily available, relative wages will increase, and human labor tasks will become relatively more expensive, furthering automation. This implication is based on the assumption of a fixed supply of labor. A future elaboration of our model could relax this assumption. If labor supply is flexible, then higher

$$p_H \frac{\sigma}{\sigma-1}\left(\int_{N-1}^{N} h(z)^{\frac{\sigma-1}{\sigma}} dz\right)^{\frac{\sigma}{\sigma-1}-1}$$
$$\frac{\sigma-1}{\sigma} h(z)^{\frac{\sigma-1}{\sigma}-1} - p_h(z) = 0$$
$$p_H \left(\int_{N-1}^{N} h(z)^{\frac{\sigma-1}{\sigma}} dz\right)^{\frac{\sigma}{\sigma-1}-1}$$
$$h(z)^{\frac{\sigma-1}{\sigma}-1} = p_h(z)$$
$$p_H \left(\int_{N-1}^{N} h(z)^{\frac{\sigma-1}{\sigma}} dz\right)^{\frac{1}{\sigma-1}}$$
$$h(z)^{-\frac{1}{\sigma}} = p_h(z)$$
$$p_H H^{\frac{1}{\sigma}} h(z)^{-\frac{1}{\sigma}} = p_h(z)$$

arriving at

$$h(z) = \frac{H}{p_h(z)^{\sigma}} p_H^{\sigma}, \tag{11}$$

see (11).

Demand for task z: Using marginal production and productivity rules

$h(z_{IT}) = A_{IT}\gamma_{IT}(z)b_{IT}(z)$	production(5)	$h(z_L) = A_L\gamma_L(z)l_L(z)$
$p_h A_{IT}\gamma_{IT}(z)b_{IT}(z) = b_{IT}(z)w_{IT}$	marginal productivity and factor reward+	$p_h A_L\gamma_L(z)l_L(z) = l_L(z)w_L$
$p_h(z_{IT}) = \frac{w_{IT}}{A_{IT}\gamma_{IT}(z_{IT})}$	price = unit labor costs	$p_h(z_L) = \frac{w_L}{A_L\gamma_L(z_L)}$

wages for labor could incentivize AI workers to work as regular workers, which will in turn, reduce the incentives to automate.

Appendix

Efficient production of human services

Optimal allocation within the task approach: Human service firms :

$$\begin{aligned} \max : \pi_H &= p_H H - p_h(z)h(z) \\ &= p_H \left(\int_{N-1}^{N} h(z)^{\frac{\sigma-1}{\sigma}} dz\right)^{\frac{\sigma}{\sigma-1}} \\ &\quad - p_h(z)h(z). \end{aligned}$$

F.O.C.

and plugging in gives (12) as being the optimal demand for $h(z)$,

$$h(z) = \frac{H}{\left(\frac{w_{IT}}{A_{IT}\gamma_{IT}(z)}\right)^{\sigma}} p_H^{\sigma}, \qquad h(z) = \frac{H}{\left(\frac{w_L}{A_L\gamma_L(z)}\right)^{\sigma}} p_H^{\sigma},$$
$$h(z) = p_H^{\sigma} H \left(\frac{A_{IT}}{w_{IT}}\right)^{\sigma} \gamma_{IT}(z)^{\sigma}, \; h(z) = p_H^{\sigma} H \left(\frac{A_L}{w_L}\right)^{\sigma} \gamma_L(z)^{\sigma}. \tag{12}$$

Demand for each kind of labor in task z: In order to determine the marginal productivity for each total labor input, the productivity for each kind of labor is derived from (12) and (5), and we can obtain the optimal demand for IT labor :

$$A_{IT}\gamma_{IT}(z)b_{IT}(z) = h(z) = p_H^{\sigma} H \left(\frac{A_{IT}}{w_{IT}}\right)^{\sigma} \gamma_{IT}(z)^{\sigma},$$

$$b_{IT}(z) = \begin{cases} \left(\frac{p_H}{w_{IT}}\right)^{\sigma} H (A_{IT})^{\sigma-1} \gamma_{IT}(z)^{\sigma-1} & \text{if } z \in [N-1, N_{IT}] \\ 0 & \text{if } z \in [N_{IT}, N] \end{cases} \tag{13}$$

and standard labor:

$$A_L \gamma_L(z) l_L(z) = h(z) = p_H^\sigma H \left(\frac{A_L}{w_L}\right)^\sigma \gamma_L(z)^\sigma$$

$$l_L(z) = \begin{cases} 0 & \text{if } z \in [N-1, N_{IT}] \\ \left(\frac{p_H}{w_L}\right)^\sigma H(A_L)^{\sigma-1}\gamma_L(z)^{\sigma-1} & \text{if } z \in (N_{IT}, N] \end{cases} \tag{14}$$

Total IT labor is fully employed and allocates to all tasks using IT labor. This holds for standard labor respectively

$$B_{IT} = \int_{N-1}^{N_{IT}} b_{IT}(z)dz, \text{ and} \tag{15}$$

$$L_L = \int_{N_{IT}}^{N} l_L(z)dz. \tag{16}$$

Income of IT expert w_{IT}: expert With the integral in (13) $[b_{IT}(z) = \frac{p_H^\sigma}{w_{IT}^\sigma} H\gamma_{IT}(z)^{\sigma-1}(A_{IT})^{\sigma-1}]$ we obtain

$$\begin{aligned}\int_{N-1}^{N_{IT}} l_{IT}(z)dz &= \int_{N-1}^{N_{IT}} \frac{p_H^\sigma}{w_{IT}^\sigma} H\gamma_{IT}(z)^{\sigma-1}(A_{IT})^{\sigma-1}dz \\ B_{IT} &= \frac{p_H^\sigma}{w_{IT}^\sigma} H(A_{IT})^{\sigma-1}\int_{N-1}^{N_{IT}} \gamma_{IT}(z)^{\sigma-1}dz \\ w_{IT}^\sigma &= p_H^\sigma \frac{H}{B_{IT}}(A_{IT})^{\sigma-1}\int_{N-1}^{N_{IT}} \gamma_{IT}(z)^{\sigma-1}dz\end{aligned}$$

such that with full employed IT labor we can determine the wages of IT labor as

$$w_{IT} = p_H \left(\frac{H}{B_{IT}}\right)^{\frac{1}{\sigma}} (A_{IT})^{\frac{\sigma-1}{\sigma}} \left(\int_{N-1}^{N_{IT}} \gamma_{IT}(z)^{\sigma-1}dz\right)^{\frac{1}{\sigma}}, \tag{17}$$

Symmetrically for standard labor,

$$\begin{aligned}\int_{N_{IT}}^{N} l_L(z)dz &= \int_{N_{IT}}^{N} \frac{p_H^\sigma}{w_{IT}^\sigma} H\gamma_{IT}(z)^{\sigma-1}(A_{IT})^{\sigma-1}dz \\ B_{IT} &= \frac{p_H^\sigma}{w_{IT}^\sigma} H(A_{IT})^{\sigma-1}\int_{N_{IT}}^{N} \gamma_{IT}(z)^{\sigma-1}dz \\ w_{IT}^\sigma &= p_H^\sigma \frac{H}{L_{IT}}(A_{IT})^{\sigma-1}\int_{N_{IT}}^{N} \gamma_{IT}(z)^{\sigma-1}dz\end{aligned}$$

$$w_L = p_H \left(\frac{H}{L_L}\right)^{\frac{1}{\sigma}} (A_L)^{\frac{\sigma-1}{\sigma}} \left(\int_{N_{IT}}^{N} \gamma_L(z)^{\sigma-1}dz\right)^{\frac{1}{\sigma}}. \tag{18}$$

The resulting internal relative factor productivity for labor is:

$$\begin{aligned}\frac{w_L}{w_{IT}} &= \frac{\left(\frac{p_H H}{L_L}\right)^{\frac{1}{\sigma}} (A_L)^{\frac{\sigma-1}{\sigma}} \left(\int_{N_{IT}}^{N} \gamma_L(z)^{\sigma-1}dz\right)^{\frac{1}{\sigma}}}{\left(\frac{p_H H}{L_{IT}}\right)^{\frac{1}{\sigma}} (A_{IT})^{\frac{\sigma-1}{\sigma}} \left(\int_{N-1}^{N_{IT}} \gamma_{IT}(z)^{\sigma-1}dz\right)^{\frac{1}{\sigma}}} \\ \frac{w_L}{w_{IT}} &= \left(\frac{B_{IT}}{L_L}\right)^{\frac{1}{\sigma}} \left(\frac{A_L}{A_{IT}}\right)^{\frac{\sigma-1}{\sigma}} \left(\frac{\int_{N_{IT}}^{N} \gamma_L(z)^{\sigma-1}dz}{\int_{N-1}^{N_{IT}} \gamma_{IT}(z)^{\sigma-1}dz}\right)^{\frac{1}{\sigma}}\end{aligned}$$

Endogenous switch to AI/automated tasks N_{IT} : From the discussion of (6) it is known that tasks are ordered such that $\gamma(z) = \frac{\gamma_L(z)}{\gamma_{IT}(z)}$, and $\frac{\partial\gamma(z)}{\partial z} > 0$. If it is assumed that task N_{IT} is the task that exactly separates the production mode, and if tasks are continues, the condition (6) can be rewritten as follows:

$$\begin{aligned}&\frac{A_L\gamma_L(N_{IT})}{A_{IT}\gamma_{IT}(N_{IT})} < \frac{w_L}{w_{IT}} \\ &= \left(\frac{B_{IT}}{L_L}\right)^{\frac{1}{\sigma}} \left(\frac{A_L}{A_{IT}}\right)^{\frac{\sigma-1}{\sigma}} \\ &\left(\frac{\int_{N_{IT}}^{N} \gamma_L(z)^{\sigma-1}dz}{\int_{N-1}^{N_{IT}} \gamma_{IT}(z)^{\sigma-1}dz}\right)^{\frac{1}{\sigma}} \\ &0 = G = \gamma(N_{IT}) - \left(\frac{A_{IT}B_{IT}}{A_L L_L}\right)^{\frac{1}{\sigma}} \\ &\left(\frac{\int_{N_{IT}}^{N} \gamma_L(z)^{\sigma-1}dz}{\int_{N-1}^{N_{IT}} \gamma_{IT}(z)^{\sigma-1}dz}\right)^{\frac{1}{\sigma}}\end{aligned} \tag{19}$$

If $\frac{dG}{dN_{IT}} \neq 0$, G implicitly defines a function $N_{IT} = N_{IT}(B_{IT}, L_L, A_{IT}, ...)$. Thus, we need to calculate the respective derivatives.

$$\begin{aligned}\frac{dG}{dN_{IT}} &= \frac{\partial\gamma(N_{IT})}{\partial N_{IT}} \\ &+ \left[\begin{array}{c} \frac{1}{\sigma}\left(\frac{A_{IT}B_{IT}}{A_L L_L}\right)^{\frac{1}{\sigma}} \left(\frac{\int_{N_{IT}}^{N} \gamma_L(z)^{\sigma-1}dz}{\int_{N-1}^{I} \gamma_{IT}(z)^{\sigma-1}dz}\right)^{\frac{1}{\sigma}} \\ \left[\frac{\gamma_L(N_{IT})^{\sigma-1}}{\int_{N_{IT}}^{N} \gamma_L(N_{IT})^{\sigma-1}dz} + \frac{\gamma_{IT}(N_{IT})^{\sigma-1}}{\int_{N-1}^{N_{IT}} \gamma_{IT}(N_{IT})^{\sigma-1}dz}\right]\end{array}\right] > 0\end{aligned}$$

and defining $\Gamma_{IT}(N_{IT}) = \int_{N-1}^{N_{IT}} \gamma_{IT}(z)^{\sigma-1}dz$, $\frac{d\Gamma_{IT}}{dN_{IT}} = \gamma_{IT}(N_{IT})^{\sigma-1}$; and $\Gamma_L(N_{IT}) = \int_{N_{IT}}^{N} \gamma_L(z)^{\sigma-1}dz$, $\frac{d\Gamma_L}{dN_{IT}} = -\gamma_L(N_{IT})^{\sigma-1}$ we obtain

$$\frac{\partial G}{\partial N_{IT}} = \frac{\partial \gamma(N_{IT})}{\partial N_{IT}} + \frac{1}{\sigma}\left(\frac{A_{IT}B_{IT}}{A_L L_L}\right)^{\frac{1}{\sigma}}\left(\frac{\Gamma_L(N_{IT})}{\Gamma_{IT}(N_{IT})}\right)^{\frac{1}{\sigma}} \left[\frac{\gamma_L(N_{IT})^{\sigma-1}}{\Gamma_L(N_{IT})} + \frac{\gamma_{IT}(N_{IT})^{\sigma-1}}{\Gamma_{IT}(N_{IT})}\right] > 0$$

$$\frac{\partial G}{\partial A_{IT}} = -\frac{1}{\sigma}\left(\frac{A_{IT}B_{IT}}{A_L L_L}\right)^{\frac{1}{\sigma}-1}\left(\frac{\Gamma_L(N_{IT})}{\Gamma_{IT}(N_{IT})}\right)^{\frac{1}{\sigma}} \frac{B_{IT}}{A_L L_L} < 0$$

and the derivative of the implicit function $N_{IT} = N_{IT}(A_{IT})$ is

$$\frac{dN_{IT}}{dA_{IT}} = -\frac{\frac{\partial G}{\partial A_{IT}}}{\frac{\partial G}{\partial N_{IT}}} > 0$$

More specific:

$$H = \left(\int_{N-1}^{N_{IT}} h(z)^{\frac{\sigma-1}{\sigma}}dz + \int_{N_{IT}}^{N} h(z)^{\frac{\sigma-1}{\sigma}}dz\right)^{\frac{\sigma}{\sigma-1}}$$

$$= \left(\int_{N-1}^{N_{IT}} \left(p_H^{\sigma} H\left(\frac{A_{IT}}{w_{IT}}\right)^{\sigma}\gamma_I(z)^{\sigma}\right)^{\frac{\sigma-1}{\sigma}} dz + \int_{N_{IT}}^{N} \left(p_H^{\sigma} H\left(\frac{A_L}{w_L}\right)^{\sigma}\gamma_L(z)^{\sigma}\right)^{\frac{\sigma-1}{\sigma}} dz\right)^{\frac{\sigma}{\sigma-1}}.$$

Using (17) and (18) results in: $w_{IT} = p_H\left(\frac{H}{B_{IT}}\right)^{\frac{1}{\sigma}}(A_{IT})^{\frac{\sigma-1}{\sigma}}\left(\int_{N-1}^{N_{IT}}\gamma_{IT}(z)^{\sigma-1}dz\right)^{\frac{1}{\sigma}}$

$$\frac{dN_{IT}}{dA_{IT}} = \frac{\frac{1}{\sigma}\left(\frac{A_{IT}B_{IT}}{A_L L_L}\right)^{\frac{1}{\sigma}}\left(\frac{\Gamma_L(N_{IT})}{\Gamma_{IT}(N_{IT})}\right)^{\frac{1}{\sigma}}\frac{1}{A_{IT}}}{\frac{\partial\gamma(N_{IT})}{\partial N_{IT}} + \frac{1}{\sigma}\left(\frac{A_{IT}B_{IT}}{A_L L_L}\right)^{\frac{1}{\sigma}}\left(\frac{\Gamma_L(N_{IT})}{\Gamma_{IT}(N_{IT})}\right)^{\frac{1}{\sigma}}\left[\frac{\gamma_L(N_{IT})^{\sigma-1}}{\Gamma_L(N_{IT})} + \frac{\gamma_{IT}(N_{IT})^{\sigma-1}}{\Gamma_{IT}(N_{IT})}\right]}$$

$$\eta_{N_{IT},A_{IT}} = \frac{dN_{IT}}{dA_{IT}}\frac{A_{IT}}{N_{IT}} = \frac{1}{\sigma\frac{\partial\gamma(N_{IT})}{\partial N_{IT}}\left(\frac{A_L L_L}{A_{IT}B_{IT}}\frac{\Gamma_{IT}(N_{IT})}{\Gamma_L(N_{IT})}\right)^{\frac{1}{\sigma}} + \frac{\gamma_L(N_{IT})^{\sigma-1}}{\Gamma_L(N_{IT})} + \frac{\gamma_{IT}(N_{IT})^{\sigma-1}}{\Gamma_{IT}(N_{IT})}}\frac{1}{N_{IT}}$$

Total supply of human service inputs

From (12) it is known that $h(z) = p_H^{\sigma} H\left(\frac{A_{IT}}{w_{IT}}\right)^{\sigma}\gamma_{IT}(z)^{\sigma}$ for $z \in [N-1, N_{IT}.$, and $h(z) = p_H^{\sigma} H\left(\frac{A_L}{w_L}\right)^{\sigma}\gamma_L(z)^{\sigma}$ for $z \in [N_{IT}, N]$. Plugging this in (4) generates an expression for the total value of H:

$$H = \left(\int_{N-1}^{N_{IT}} \left(\gamma_{IT}(z)^{\sigma}\right)^{\frac{\sigma-1}{\sigma}} dz \left(p_H^{\sigma} H\left(\frac{A_{IT}}{w_{IT}}\right)^{\sigma}\right)^{\frac{\sigma-1}{\sigma}} + \int_{N_{IT}}^{N}\left(\gamma_L(z)^{\sigma}\right)^{\frac{\sigma-1}{\sigma}} dz \left(p_H^{\sigma} H\left(\frac{A_L}{w_L}\right)^{\sigma}\right)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}$$

$$= \left(\int_{N-1}^{N_{IT}} \gamma_{IT}(z)^{\sigma-1} dz p_H^{\sigma-1} H^{\frac{\sigma-1}{\sigma}}\left(\frac{A_{IT}}{w_{IT}}\right)^{\sigma-1} + \int_{N_{IT}}^{N}\gamma_L(z)^{\sigma-1} dz p_H^{\sigma-1} H^{\frac{\sigma-1}{\sigma}}\left(\frac{A_L}{w_L}\right)^{\sigma-1}\right)^{\frac{\sigma}{\sigma-1}} \qquad (20)$$

$$= \left(\int_{N-1}^{N_{IT}}\gamma_{IT}(z)^{\sigma-1}dz p_H^{\sigma-1}H^{\frac{\sigma-1}{\sigma}}\left(\frac{A_{IT}}{p_H\left(\frac{H}{B_{IT}}\right)^{\frac{1}{\sigma}}(A_{IT})^{\frac{\sigma-1}{\sigma}}\left(\int_{N-1}^{N_{IT}}\gamma_{IT}(z)^{\sigma-1}dz\right)^{\frac{1}{\sigma}}}\right)^{\sigma-1} + \int_{N_{IT}}^{N}\gamma_L(z)^{\sigma-1}dz p_H^{\sigma-1}H^{\frac{\sigma-1}{\sigma}}\left(\frac{A_L}{p_H\left(\frac{H}{L_L}\right)^{\frac{1}{\sigma}}(A_L)^{\frac{\sigma-1}{\sigma}}\left(\int_{N_{IT}}^{N}\gamma_L(z)^{\sigma-1}dz\right)^{\frac{1}{\sigma}}}\right)^{\sigma-1}\right)^{\frac{\sigma}{\sigma-1}}$$

$$
= \left(\begin{array}{l} \int_{N-1}^{N_{IT}} \gamma_{IT}(z)^{\sigma-1} dz p_H^{\sigma-1} H^{\frac{\sigma-1}{\sigma}} \left(\frac{p_H^{-1} H^{-\frac{1}{\sigma}} B_{IT}^{\frac{1}{\sigma}} A_{IT}^{\frac{1}{\sigma}}}{\left(\int_{N-1}^{N_{IT}} \gamma_{IT}(z)^{\sigma-1} dz \right)^{\frac{1}{\sigma}}} \right)^{\sigma-1} \\ + \int_{N_{IT}}^{N} \gamma_L(z)^{\sigma-1} dz p_H^{\sigma-1} H^{\frac{\sigma-1}{\sigma}} \left(\frac{p_H^{-1} H^{-\frac{1}{\sigma}} L_L^{\frac{1}{\sigma}} A_L^{\frac{1}{\sigma}}}{\left(\int_{N_{IT}}^{N} \gamma_L(z)^{\sigma-1} dz \right)^{\frac{1}{\sigma}}} \right)^{\sigma-1} \end{array} \right)^{\frac{\sigma}{\sigma-1}}
$$

$$
= \left(\begin{array}{l} \int_{N-1}^{N_{IT}} \gamma_{IT}(z)^{\sigma-1} dz p_H^{\sigma-1} H^{\frac{\sigma-1}{\sigma}} \frac{p_H^{-(\sigma-1)} H^{-\frac{\sigma-1}{\sigma}} (B_{IT} A_{IT})^{\frac{\sigma-1}{\sigma}}}{\left(\int_{N-1}^{N_{IT}} \gamma_{IT}(z)^{\sigma-1} dz \right)^{\frac{\sigma-1}{\sigma}}} \\ + \int_{N_{IT}}^{N} \gamma_L(z)^{\sigma-1} dz p_H^{\sigma-1} H^{\frac{\sigma-1}{\sigma}} \frac{p_H^{-(\sigma-1)} H^{-\frac{\sigma-1}{\sigma}} (L_L A_L)^{\frac{\sigma-1}{\sigma}}}{\left(\int_{N_{IT}}^{N} \gamma_L(z)^{\sigma-1} dz \right)^{\frac{\sigma-1}{\sigma}}} \end{array} \right)^{\frac{\sigma}{\sigma-1}}
$$

$$
= \left(\int_{N-1}^{N_{IT}} \gamma_{IT}(z)^{\sigma-1} dz \frac{(B_{IT} A_{IT})^{\frac{\sigma-1}{\sigma}}}{\left(\int_{N-1}^{N_{IT}} \gamma_{IT}(z)^{\sigma-1} dz \right)^{\frac{\sigma-1}{\sigma}}} + \int_{N_{IT}}^{N} \gamma_L(z)^{\sigma-1} d \frac{(L_L A_L)^{\frac{\sigma-1}{\sigma}}}{\left(\int_{N_{IT}}^{N} \gamma_L(z)^{\sigma-1} dz \right)^{\frac{\sigma-1}{\sigma}}} \right)^{\frac{\sigma}{\sigma-1}}
$$

$$
H = \left(\left(\int_{N-1}^{N_{IT}} \gamma_{IT}(z)^{\sigma-1} dz \right)^{\frac{1}{\sigma}} (B_{IT} A_{IT})^{\frac{\sigma-1}{\sigma}} + \left(\int_{N_{IT}}^{N} \gamma_L(z)^{\sigma-1} dz \right)^{\frac{1}{\sigma}} (L_L A_L)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}
$$

Labor share of income from human services

To determine the contribution of standard labor to total service production one can start from the total amount of H:

$$
H = \left(\int_{N-1}^{N_{IT}} h(z)^{\frac{\sigma-1}{\sigma}} dz + \int_{N_{IT}}^{N} h(z)^{\frac{\sigma-1}{\sigma}} dz \right)^{\frac{\sigma}{\sigma-1}}
$$

$$
= \left(\int_{N-1}^{N_{IT}} \left(p_H^{\sigma} H \left(\frac{A_{IT}}{w_{IT}} \right)^{\sigma} \gamma_I(z)^{\sigma} \right)^{\frac{\sigma-1}{\sigma}} dz + \int_{N_{IT}}^{N} \left(p_H^{\sigma} H \left(\frac{A_L}{w_L} \right)^{\sigma} \gamma_L(z)^{\sigma} \right)^{\frac{\sigma-1}{\sigma}} dz \right)^{\frac{\sigma}{\sigma-1}}.
$$

Using (17) and (18) results in: $w_{IT} = p_H \left(\frac{H}{B_{IT}} \right)^{\frac{1}{\sigma}} (A_{IT})^{\frac{\sigma-1}{\sigma}} \left(\int_{N-1}^{N_{IT}} \gamma_{IT}(z)^{\sigma-1} dz \right)^{\frac{1}{\sigma}}$

$$
H = \left(\int_{N-1}^{N_{IT}} \left(\gamma_{IT}(z)^{\sigma} \right)^{\frac{\sigma-1}{\sigma}} dz \left(p_H^{\sigma} H \left(\frac{A_{IT}}{w_{IT}} \right)^{\sigma} \right) + \int_{N_{IT}}^{N} \left(\gamma_L(z)^{\sigma} \right)^{\frac{\sigma-1}{\sigma}} dz \left(p_H^{\sigma} H \left(\frac{A_L}{w_L} \right)^{\sigma} \right)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}
$$

$$
H = \left(\int_{N-1}^{N_{IT}} \gamma_{IT}(z)^{\sigma-1} dz p_H^{\sigma-1} H^{\frac{\sigma-1}{\sigma}} \left(\frac{A_{IT}}{w_{IT}} \right)^{\sigma-1} + \int_{N_{IT}}^{N} \gamma_L(z)^{\sigma-1} dz p_H^{\sigma-1} H^{\frac{\sigma-1}{\sigma}} \left(\frac{A_L}{w_L} \right)^{\sigma-1} \right)^{\frac{\sigma}{\sigma-1}}
$$

$$
1 = \left(\int_{N-1}^{N_{IT}} \gamma_{IT}(z)^{\sigma-1} dz \left(\frac{A_{IT}}{w_{IT}} \right)^{\sigma-1} + \int_{N_{IT}}^{N} \gamma_L(z)^{\sigma-1} dz \left(\frac{A_L}{w_L} \right)^{\sigma-1} \right)^{\frac{\sigma}{\sigma-1}} p_H^{\sigma}
$$

Plugging in definitions $\Gamma_L(N_{IT}, N) = \int_{N_{IT}}^{N} \gamma_L(z)^{\sigma-1} dz = \Gamma(N_{IT}, N) \Pi(N_{IT}, N)^{\sigma-1}$ and $\Gamma_{IT}(N_{IT}, N) = \int_{N-1}^{N_{IT}} \gamma_{IT}(z)^{\sigma-1} dz = (1 - \Gamma(N_{IT}, N)) \Pi(N_{IT}, N)^{\sigma-1}$ we obtain

$$
1 = \left(\Gamma_{IT}(N_{IT}, N) \left(\frac{A_{IT}}{w_{IT}} \right)^{\sigma-1} + \Gamma_L(N_{IT}, N) \left(\frac{A_L}{w_L} \right)^{\sigma-1} \right)^{\frac{\sigma}{\sigma-1}} p_H^{\sigma}
$$

$$
1 = \left(\frac{\Gamma_{IT}(N_{IT}, N)}{\Gamma_L(N_{IT}, N)} \frac{\left(\frac{A_{IT}}{w_{IT}} \right)^{\sigma-1}}{\left(\frac{A_L}{w_L} \right)^{\sigma-1}} + 1 \right)^{\frac{\sigma}{\sigma-1}}
$$

$$
\Gamma_L(N_{IT}, N)^{\frac{\sigma}{\sigma-1}} \left(\frac{A_L}{w_L} \right)^{\sigma} p_H^{\sigma}
$$

Rearrange this equation gives:

$$1 = \left(\frac{\Gamma_{IT}(N_{IT},N)}{\Gamma_L(N_{IT},N)} \frac{\left(\frac{A_{IT}}{w_{IT}}\right)^{\sigma-1}}{\left(\frac{A_L}{w_L}\right)^{\sigma-1}} + 1 \right)^{\frac{\sigma}{\sigma-1}} \Gamma_L(N_{IT},N)^{\frac{\sigma}{\sigma-1}} \left(\frac{A_L}{w_L}\right)^{\sigma} p_H^{\sigma} \tag{21}$$

$$\begin{aligned}
\left(\frac{A_L}{w_L}\right)^{-(\sigma-1)} p_H^{-(\sigma-1)} &= \left(\frac{\Gamma_{IT}(N_{IT},N)}{\Gamma_L(N_{IT},N)} \frac{\left(\frac{A_{IT}}{w_{IT}}\right)^{\sigma-1}}{\left(\frac{A_L}{w_L}\right)^{\sigma-1}} + 1 \right) \Gamma_L(N_{IT},N) \\
\left(\frac{A_L}{w_L}\right)^{(\sigma-1)} p_H^{(\sigma-1)} &= \frac{1}{\left(\frac{\Gamma_{IT}(N_{IT},N)}{\Gamma_L(N_{IT},N)} \frac{\left(\frac{A_{IT}}{w_{IT}}\right)^{\sigma-1}}{\left(\frac{A_L}{w_L}\right)^{\sigma-1}} + 1 \right) \Gamma_L(N_{IT},N)}
\end{aligned}$$

Further, from definition (15) the following expression can be derived

$$\begin{aligned}
L_L &= \int_{N_{IT}}^{N} \frac{p_H^{\sigma} H}{(w_L)^{\sigma}} (A_L)^{\sigma-1} \gamma_L(z)^{\sigma-1} dz \\
&= \frac{p_H^{\sigma} H}{(w_L)^{\sigma}} (A_L)^{\sigma-1} \int_{N_{IT}}^{N} \gamma_L(z)^{\sigma-1} dz.
\end{aligned}$$

Using the definition of labor share of income $\phi_L = \frac{w_L L}{p_H H}$

$$\begin{aligned}
\frac{L_L w_L}{p_H H} &= \frac{w_L}{p_H} \frac{1}{H} \frac{p_H^{\sigma} H}{(w_L)^{\sigma}} (A_L)^{\sigma-1} \int_{N_{IT}}^{N} \gamma_L(z)^{\sigma-1} dz \\
\frac{L_L w_L}{p_H H} &= \left(\frac{w_L}{p_H}\right)^{1-\sigma} (A_L)^{\sigma-1} \Gamma_L(N_{IT},N)
\end{aligned}$$

Combining this with (21) gives labor's share of income as fully depending on relative labor rewards $\frac{w_L}{w_{IT}}$

$$\begin{aligned}
\frac{L_L w_L}{p_H H} &= \left(\frac{w_L}{p_H}\right)^{1-\sigma} (A_L)^{\sigma-1} \Gamma_L(N_{IT},N) \\
&= \frac{\Gamma_L(N_{IT},N)}{\left(\frac{\Gamma_{IT}(N_{IT},N)}{\Gamma_L(N_{IT},N)} \frac{\left(\frac{A_{IT}}{w_{IT}}\right)^{\sigma-1}}{\left(\frac{A_L}{w_L}\right)^{\sigma-1}} + 1 \right) \Gamma_L(N_{IT},N)} \\
&= \left(\frac{\Gamma_{IT}(N_{IT},N)}{\Gamma_L(N_{IT},N)} \left(\frac{A_{IT}}{A_L}\right)^{\sigma-1} \left(\frac{w_L}{w_{IT}}\right)^{\sigma-1} + 1 \right)^{-1}
\end{aligned}$$

plugging in the relative factor rewards $\frac{w_L}{w_{IT}} = \left(\frac{B_{IT}}{L_L}\right)^{\frac{1}{\sigma}} \left(\frac{A_L}{A_{IT}}\right)^{\frac{\sigma-1}{\sigma}} \left(\frac{\Gamma_L(N_{IT},N)}{\Gamma_{IT}(N_{IT},N)}\right)^{\frac{1}{\sigma}}$ (see above) finally leads to

$$\begin{aligned}
\phi_L =& \left(1 + \frac{\Gamma_{IT}(N_{IT},N)}{\Gamma_L(N_{IT},N)} \left(\frac{A_{IT}}{A_L}\right)^{\sigma-1} \right. \\
& \left. \left(\left(\frac{B_{IT}}{L_L}\right)^{\frac{1}{\sigma}} \left(\frac{A_L}{A_{IT}}\right)^{\frac{\sigma-1}{\sigma}} \left(\frac{\Gamma_L(N_{IT},N)}{\Gamma_{IT}(N_{IT},N)}\right)^{\frac{1}{\sigma}} \right)^{\sigma-1} \right)^{-1} \\
=& \left(1 + \frac{\Gamma_{IT}(N_{IT},N)}{\Gamma_L(N_{IT},N)} \left(\frac{\Gamma_{IT}(N_{IT},N)}{\Gamma_L(N_{IT},N)}\right)^{-\frac{\sigma-1}{\sigma}} \right. \\
& \left. \left(\left(\frac{B_{IT}}{L_L}\right)^{\frac{1}{\sigma}} \left(\frac{A_L}{A_{IT}}\right)^{\frac{\sigma-1}{\sigma}} \left(\frac{A_{IT}}{A_L}\right) \right)^{\sigma-1} \right)^{-1} \\
=& \left(1 + \frac{\Gamma_{IT}(N_{IT},N)}{\Gamma_L(N_{IT},N)}^{\frac{1}{\sigma}} \left(\left(\frac{B_{IT}}{L_L}\right)^{\frac{1}{\sigma}} \left(\frac{A_L}{A_{IT}}\right)^{\frac{\sigma-1}{\sigma}} \left(\frac{A_L}{A_{IT}}\right)^{-\frac{\sigma}{\sigma}} \right)^{\sigma-1} \right)^{-1},
\end{aligned}$$

which results in the labor share of income from human services:

$$\phi_L = \frac{w_L L_L}{p_H H} = \left(1 + \frac{\Gamma_{IT}(N_{IT},N)}{\Gamma_L(N_{IT},N)}^{\frac{1}{\sigma}} \left(\frac{B_{IT}}{L_L} \frac{A_{IT}}{A_L}\right)^{\frac{\sigma-1}{\sigma}} \right)^{-1}$$

Derivative with respect to A_{IT}:

We first take the derivatives of Γ_{IT} and Γ_L,

$$\begin{aligned}
\Gamma_{IT}(N_{IT},N) &= \int_{N-1}^{N_{IT}} \gamma_{IT}(z)^{\sigma-1} dz =, \frac{d\Gamma_{IT}}{dN_{IT}} = \gamma_{IT}(N_{IT})^{\sigma-1} \\
\Gamma_L(N_{IT},N) &= \int_{N_{IT}}^{N} \gamma_L(z)^{\sigma-1} dz =, \frac{d\Gamma_L}{dN_{IT}} = -\gamma_L(N_{IT})^{\sigma-1}.
\end{aligned}$$

Taking the derivative for the labor share of income and using the $\eta_{\phi_L,A_{IT}} = \frac{d\phi_L}{dA_{IT}} \frac{A_{IT}}{\phi_L}$ definition gives:

$$\frac{d\phi_L}{dA_{IT}} = -\frac{1}{(...)^2}\left(\frac{B_{IT}}{L_L}\right)^{\frac{\sigma-1}{\sigma}} \left[\begin{array}{c} \frac{\sigma-1}{\sigma}\left(\frac{\Gamma_{IT}(N_{IT},N)}{\Gamma_L(N_{IT},N)}\right)^{\frac{1}{\sigma}}\left(\frac{A_{IT}}{A_L}\right)^{\frac{\sigma-1}{\sigma}-1}\frac{1}{A_L} \\ +\frac{1}{\sigma}\left(\frac{A_{IT}}{A_L}\right)^{\frac{\sigma-1}{\sigma}}\left(\frac{\Gamma_{IT}(N_{IT},N)}{\Gamma_L(N_{IT},N)}\right)^{\frac{1}{\sigma}-1}\left(\begin{array}{c} \frac{\frac{d\Gamma_{IT}}{dN_{IT}}\frac{dN_{IT}}{dA_{IT}}}{\Gamma_L(N_{IT},N)} \\ -\frac{\Gamma_{IT}(N_{IT},N)\frac{d\Gamma_L}{dN_{IT}}\frac{dN_{IT}}{dA_{IT}}}{\Gamma_L(N_{IT},N)^2} \end{array} \right) \end{array} \right]$$

$$\frac{d\phi_L}{dA_{IT}}\frac{1}{\phi_L} = -\frac{\left(\frac{B_{IT}}{L_L}\right)^{\frac{\sigma-1}{\sigma}}}{(...)\sigma} \left[\begin{array}{c} (\sigma-1)\left(\frac{\Gamma_{IT}(N_{IT},N)}{\Gamma_L(N_{IT},N)}\right)^{\frac{1}{\sigma}}\left(\frac{A_{IT}}{A_L}\right)^{\frac{\sigma-1}{\sigma}-1}\frac{1}{A_L} \\ +\left(\frac{A_{IT}}{A_L}\right)^{\frac{\sigma-1}{\sigma}}\left(\frac{\Gamma_{IT}(N_{IT},N)}{\Gamma_L(N_{IT},N)}\right)^{\frac{1}{\sigma}-1}\frac{\Gamma_{IT}(N_{IT},N)}{\Gamma_L(N_{IT},N)}\left(\begin{array}{c} \frac{d\Gamma_{IT}}{dN_{IT}}\frac{1}{\Gamma_{IT}(N_{IT},N)}\frac{dN_{IT}}{dA_{IT}} \\ -\frac{d\Gamma_L}{dN_{IT}}\frac{1}{\Gamma_L(N_{IT},N)}\frac{dN_{IT}}{dA_{IT}} \end{array} \right) \end{array} \right]$$

$$\eta_{\phi_L,A_{IT}} = \frac{-\left(\frac{B_{IT}}{L_L}\right)^{\frac{\sigma-1}{\sigma}}\left(\frac{\Gamma_{IT}(N_{IT},N)}{\Gamma_L(N_{IT},N)}\right)^{\frac{1}{\sigma}}\left(\frac{A_{IT}}{A_L}\right)^{\frac{\sigma-1}{\sigma}}}{(...)\sigma}\left[(\sigma-1)+\left(\begin{array}{c} \frac{d\Gamma_{IT}}{dN_{IT}}\frac{N_{IT}}{\Gamma_{IT}(N_{IT},N)}\frac{dN_{IT}}{dA_{IT}}\frac{A_{IT}}{N_{IT}} \\ -\frac{d\Gamma_L}{dN_{IT}}\frac{N_{IT}}{\Gamma_L(N_{IT},N)}\frac{dN_{IT}}{dA_{IT}}\frac{A_{IT}}{N_{IT}} \end{array} \right)\right]$$

$$\eta_{\phi_L,A_{IT}} = \frac{-\left(\frac{B_{IT}}{L_L}\right)^{\frac{\sigma-1}{\sigma}}\left(\frac{\Gamma_{IT}(N_{IT},N)}{\Gamma_L(N_{IT},N)}\right)^{\frac{1}{\sigma}}\left(\frac{A_{IT}}{A_L}\right)^{\frac{\sigma-1}{\sigma}}}{\left(\left(\frac{B_{IT}}{L_L}\right)^{\frac{\sigma-1}{\sigma}}\left(\frac{A_{IT}}{A_L}\right)^{\frac{\sigma-1}{\sigma}}\left(\frac{\Gamma_{IT}(N_{IT},N)z}{\Gamma_L(N_{IT},N)}\right)^{\frac{1}{\sigma}}+1\right)\sigma} \left[(\sigma-1)+\left(\begin{array}{c} \frac{\gamma_{IT}(N_{IT})^{\sigma-1}}{\Gamma_{IT}(N_{IT},N)} \\ +\frac{\gamma_L(N_{IT})^{\sigma-1}}{\Gamma_L(N_{IT},N)} \end{array} \right)N_{IT}\eta_{N_{IT},A_{IT}}\right]$$

$$\eta_{\phi_L,A_{IT}} = \frac{-1}{\sigma}\frac{(\sigma-1)+\left(\frac{\gamma_{IT}(N_{IT})^{\sigma-1}}{\Gamma_{IT}(N_{IT},N)}+\frac{\gamma_L(N_{IT})^{\sigma-1}}{\Gamma_L(N_{IT},N)}\right)N_{IT}\eta_{N_{IT},A_{IT}}}{1+\left(\frac{A_L L_L}{A_{IT}B_{IT}}\right)^{\frac{\sigma-1}{\sigma}}\left(\frac{\Gamma_L(N_{IT},N)}{\Gamma_{IT}(N_{IT},N)}\right)^{\frac{1}{\sigma}}} < 0.$$

For $1 < \sigma$ the share will clearly decline, $\eta_{\phi_L,A_{IT}} < 0$ If $1 > \sigma$ the share will not necessarily increase. Introducing more IT tasks$-\left(\frac{\gamma_{IT}(N_{IT})^{\sigma-1}}{\Gamma_{IT}(N_{IT},N)}+\frac{\gamma_L(N_{IT})^{\sigma-1}}{\Gamma_L(N_{IT},N)}\right)N_{IT}\eta_{N_{IT},A_{IT}} < 0$ will decrease the share of labor income and overcompensate the potentially positive effect from complementarity, $1 > \sigma$.

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