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TECHNOLOGY ADOPTION AND SPECIALIZED LABOR

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Technology adoption and specialized labor*

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Abstract

Empirical evidence identifies shortages of specialized labor as one of the main obstacles to technology adoption. In this paper, we explain this phenomenon by developing a model in which firms require specialized labor to produce with a new (more efficient) technology. We assume that the cost of specializing labor increases with the efficiency gains that can be attained through the new technology. This reveals two opposing effects on the endogenous share of specialized labor. On the one hand, there is a *wage effect* by which efficiency gains widen the wage gap between specialized and unspecialized workers, raising the share of specialized labor. On the other hand, there is a *learning effect* by which efficiency gains increase specialization costs, reducing the share of specialized labor. We show the *learning effect* will dominate when firms have sufficient market power.

JEL CODES: O33; J24; I26 KEYWORDS: Technology adoption - education - product differentiation

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Résumé non technique

L'adoption de nouvelles technologies influence la productivité, l'emploi, la concurrence et donc l'évolution des prix. Alors que des nouvelles technologies plus performantes sont déjà disponibles, les entreprises hésitent souvent à les adopter, en citant une pénurie de main-d'œuvre spécialisée. En effet, une récente enquête de la BEI identifie la "disponibilité de personnel qualifié" comme l'obstacle à l'investissement le plus cité par les entreprises de la zone euro. Une enquête de la BCE confirme que le "recrutement et la rétention de personnel hautement qualifié" est l'un des principaux obstacles à l'adoption des technologies numériques dans la zone euro. Au Luxembourg, le rapport PwC concernant le secteur bancaire souligne la concurrence pour les talents et le développement des compétences du personnel comme les principaux défis pour les banques.

Dans ce contexte, cet article développe un modèle théorique pour déterminer la part de main-d'œuvre qui choisit de se spécialiser et donc le niveau d'adoption des nouvelles technologies. L'adoption de ces nouvelles technologies exige une formation qui est coûteuse pour les employeurs ainsi que pour les employés. Les employés assumeront le coût de spécialisation uniquement s'ils peuvent s'attendre à une compensation en termes de salaires. La concurrence entre entreprises détermine le niveau des salaires, ce qui fixe les incitations pour la spécialisation de la main-d'œuvre et peut donc faciliter l'adoption de technologies plus efficaces. En général, on pourrait s'attendre à ce que la part des travailleurs spécialisés augmente avec l'efficacité de la nouvelle technologie. Cependant, le modèle montre que le contraire est aussi possible. En fait, une nouvelle technologie sera adoptée seulement si elle permet une hausse des salaires suffisante pour inciter les travailleurs à se spécialiser.

1 Introduction

The process by which new technologies are adopted determines the evolution of productivity, employment, and competition. Firms often fail to adopt more efficient technologies when they become available, preferring to continue production with old technologies (see Battiati et al., 2021). Digitalization is the most recent example of new technologies that are often not adopted despite their potential for significant benefits, with many leading firms citing the lack of specialized labor as an obstacle to their adoption.[1] A recent EIB survey reports that the "availability of skilled staff" is the most cited barrier to investment by firms based in the euro area and the US.[2] Similar concerns have been raised in an ECB survey of leading euro area companies confirming that "recruitment and retention of highly skilled ICT staff" is one of the main obstacles to the adoption of digital technologies (Elding and Morris, 2018). Many respondents also reported the "development of skills among staff" as an obstacle to technology adoption.[3] Likewise, the 2019 PwC report concerning the banking sector in Luxembourg, a highly developed international financial center, highlights competition for talent and the upskilling of the workforce as the main challenges faced by banks.[4]

In this context, we develop a theoretical model to analyze the source of shortages in specialized labor and their effects on technology diffusion. New technologies often require substantial training to be properly implemented, and training is costly for both employers and employees. Workers will be willing to incur the education costs associated with new technologies only if they expect sufficient returns in future wages. Therefore, technology

[1] Beaudry et al. (2010) find lower adoption of personal computers in US metropolitan areas with less skilled labor. See Brunello and Wruuck (2021) for a recent review of the literature on skill shortages and skill mismatch in Europe.

[2] See EIB Investment Survey 2021.

[3] Consolo et al. (2021) indicate skills shortages as one of the main explanations for the low productivity gains from digitalisation.

[4] According to the PwC report *"Banking in Luxembourg Trends Figures 2019"*, 74% of banking CEOs find that it has become more challenging to hire workers and 73% link this challenge to a deficit in the supply of skilled labor. The report highlights the heterogeneity of skills among bank employees with 42% of CEOs reporting challenges to retain or develop their workforce.

adoption will not occur if the benefit of new technologies does not increase wages sufficiently to persuade workers to specialize. We find that the competitive environment plays a key role in determining the supply of specialized labor and therefore the adoption of more efficient technologies. In general, we expect the supply of specialized labor to increase with more efficient new technologies. However, we show that if products are sufficiently differentiated, the supply of specialized workers can actually decrease in the efficiency gains of the new technology. Our result is consistent with theoretical predictions. These indicate that technology adoption can be easier when products are less differentiated (see Milliou and Petrakis, 2011), and also that product substitutability fosters process innovation (Vives, 2008). Empirical support to these predictions have been found by Beneito et al. (2015). Intuitively, with heterogeneous firms, a decrease in product substitutability benefits the most efficient firms, as they enjoy larger demand effects.[5]

More specifically, we propose a Dixit-Stiglitz model featuring endogenous education to assess the role of skilled labor shortages as obstacles to technology adoption. In the model there are two technologies for production. A standard technology and a new (more efficient) technology, which allows firms to produce more output with the same amount of capital. Firms can adopt the new technology only by recruiting specialized labor. The cost of specialization varies across workers depending on their idiosyncratic ability. It is reasonable to assume a positive relationship between the required learning effort and the efficiency gains associated with the new technology. This leads to two opposing effects on education incentives. Not only do the efficiency gains increase the wage gap between specialized and unspecialized labor (positive *wage effect*), but they also increase the average specialization cost (negative *learning effect*). When the first effect dominates, the supply of specialized labor will increase in the relative efficiency of the new technology.

[5] See Melitz (2003), who was the first to show that the profit of most efficient firms increases with the degree of substitutability. The same relationship between product differentiation and firms profits can also emerge in different competitive setups. For instance, in a differentiated duopoly, Zanchettin (2006) demonstrates that the most efficient firm can benefit when products are less differentiated.

In this case, firms can offer a sufficient wage gap to incite workers to specialize, and the number of firms employing the new technology increases. However, if products are enough differentiated, the learning effect dominates. The wage gap is not sufficient to compensate workers for the increased education cost, and the supply of specialized labor declines. Despite the efficiency gains, few firms adopt the new technology. This result is consistent with He et al. (2021), who find that banks operating in areas with more skilled labor are less likely to spend in outsourced IT services, suggesting that skilled labor is a vehicle for in-house development of new technologies.

This paper relates to the literature focusing on technology adoption under imperfect competition (see Stoneman and Ireland, 1983). Some authors considered the role of uncertainty in models of oligopolistic competition. Elberfeld and Nti (2004) noticed that the uncertainty associated with the large investments required for the adoption of new technologies, may decrease the number of innovating firms. Similarly, Zhang (2020) analyzed how different degrees of uncertainty may affect technology adoption.[6] These papers focus on the uncertainty associated with large investments to explain the slow adoption of new technologies. Instead, we find that education costs can be an obstacle to technology adoption even when there is no uncertainly at all.

Yeaple (2005) considers technology adoption in a monopolistic competition setup. He shows that firms adopting better technologies pay higher wages and that international trade increases the proportion of firms adopting the new technology. Bustos (2011) includes technology upgrading into the model developed by Melitz (2003), and shows that trade liberalization fosters technology adoption. Neither of these papers accounts for education choices. Unlike these contributions, we model technology adoption based on endogenous education choices rather than uncertainty or trade liberalization.

We are not the first to focus on the role of education in technology adoption. Krueger and Kumar (2004) find that education choices are one of the main factors explaining

[6] See also Zhang et al. (2014) and Hattori and Tanaka (2017).

differences in technology-driven growth between the U.S. and Europe. However, they assume that individuals have heterogeneous abilities that are uniformly distributed across the population. Our paper shows that the the shape of this distribution can determine the rate of technology diffusion. Caselli (1999) builds a growth model with technological revolutions that are either: skill-biased or de-skilling. Education choices can have different effects depending on the type of revolution. In contrast to his findings, we show that a skill-biased technological revolution can also result in slower technology adoption. Our paper also relates to Schivardi and Schmitz (2020), who show that ineffective management explains a substantial part of the missing productivity growth in Southern Europe. In their model, exogenous differences in management skills can have sizable effects on productivity. Our analysis can provides a complementary explanation, as it links the productivity gains from a new technology to skills and specialization costs.

The paper is organized as follows. Section 2 describes the model, Section 3 solves the model for a given level of technology. Section 4 analyses technology adoption decisions and Section 5 concludes.

2 The model

We model a small open economy in which monopolistically competitive firms produce for foreign consumers.[7] Local firms operate under increasing returns to scale using capital and specialized labor. Wages depend on worker specialization, which can be improved through education. We consider two levels of specialization (*low* and *high*), associated with two different technologies that can be used for production (*old* and *new*). Accordingly, we will examine how specialization decisions change when the efficiency of the new cost saving technology increases.

[7] Assuming local consumers does not change the model results. All decisions regarding specialization and technology adoption yield the same outcome even when the demand comes from local workers.

2.1 International consumers

As in previous literature (see Forslid and Ottaviano, 2003), we consider a "Dixit-Stiglitz" demand system, in which agents prefer to consume a diversified bundle of goods. Therefore, the preferences of a representative consumer can be described by the following utility function,

$$U = \left(\int_0^n c_i^{\frac{\sigma-1}{\sigma}} di \right)^{\frac{\sigma}{\sigma-1}} \quad , \tag{1}$$

where c_i is consumption of variety i, n is the mass of available varieties, and σ is the elasticity of substitution between any two varieties. The size of the international demand is exogenous and equal to I, which represents the income available to international consumers. Without loss of generality we normalize I to 1.

2.2 Firms

As is standard in this type of setting, firms are characterized by monopolistic competition. Production involves a fixed cost $f \in R^+$ in terms of labor, and a constant marginal cost, $\beta_i \in (0, 1]$, which depends on the technology employed by the firm.

Accordingly, the profit of firm i is:

$$\pi_i = (p_i - \beta_i) \cdot q_i - w \cdot f \ , \tag{2}$$

where q_i is the firm's output and p_i its unit price, while w is the wage. Each firm sets the price of its variety to maximize profits, while due to free-entry no firm earns a positive profit at the equilibrium.[8]

For simplicity, we consider two technologies (*old* and *new*) associated with marginal costs β_o and β_n, with $\beta_n < \beta_o$. Throughout the analysis of Section 4, and without loss of

[8]We expect new firms to enter if the incumbent earns a positive profit. This happens until no firm earns a positive profit. The scale of firms under free-entry is determined by the cost structure and the elasticity of substitution. In our model, similar to Forslid and Ottaviano (2003), operating profits exactly match the fixed cost paid in terms of labor.

generality, we normalize β_o to 1, so that $\beta_n = \beta \in (0, 1)$.[9]

2.3 Education decisions and technology efficiency

Workers are heterogeneous in their education cost, $x \in [1, \infty)$, which determines the disutility z of acquiring specialized education as follows: $z = (x - 1)/x$. This is similar to the approach in Delogu et al. (2018), as education costs enter logarithmically in the utility function. In this way, $z \in [0, 1]$ takes the value 0 when $x = 1$ and the value 1 when $x \to \infty$. Each worker decides whether to invest in education based on the (expected) utility of investing. Education costs are distributed according to a continuous and differentiable distribution with cumulative distribution function (c.d.f.) $F(x)$.

Although the *new* technology has the advantage of reducing marginal costs, it requires firms to hire specialized labor L_n. In order to capture the idea that a more efficient technology is more difficult to learn, we assume that the distribution of education costs depends on the efficiency parameter β, so that $F(x, \beta)$ with $\frac{\partial F(x,\beta)}{\partial \beta} > 0$. Accordingly, the less efficient the technology (the higher the β), the higher the share of workers with low specialization costs.

3 Analysis

In this section, we first discuss the case when only one technology is available for production. This allows us to focus on production and consumption. Then, we consider the model in which two technologies are available and analyze the workers' education decision.

3.1 Consumption and production with a single technology

The representative international consumer maximizes utility subject to a budget constraint by choosing the amount of each variety i taking into account its price, p_i.

[9] Elberfeld and Götz (2002) and Ago et al. (2017) made similar modelling choices.

Formally,

$$\max_{\{[c_i]_{i=0}^{n}\}} \quad \left[\int_0^n c_i^{\frac{\sigma-1}{\sigma}} di\right]^{\frac{\sigma}{\sigma-1}} \tag{3}$$
$$\text{s.t.} \quad 1 = \int_0^n p_i c_i di$$

Accordingly, the demand for variety i is:

$$c_i = \left(\frac{p_i}{P}\right)^{-\sigma} \frac{1}{P} \ , \tag{4}$$

where $P = \left[\int_0^n p_i^{1-\sigma} di\right]^{\frac{1}{1-\sigma}}$ is the price index.

Each firm sets the price of the variety it produces to maximize its profit (equation (2)),

$$p_i = \frac{\sigma}{\sigma - 1}\beta_i \ . \tag{5}$$

The optimal pricing strategy is a proportional mark-up on the marginal cost, independent of other firms' strategies. It follows from equation (5) that, the more efficient the production technology (smaller β_i), the lower the price. Therefore, as we will see in the following section, varieties produced with more advanced technologies will be sold at a lower price.

Finally, the free entry condition of zero profits determines the labor market wage,

$$\pi_i = 0 \longrightarrow w = \frac{q_i(p_i - \beta_i)}{f}. \tag{6}$$

Notice that the efficiency of the production technology (i.e., decreasing β_i) should have a positive effect on wages. Therefore, if different technologies are available for production, we will expect relatively higher wages paid by firms employing more advanced technologies. However, this is not apparent when only one technology is available. In this case, every variety has the same price and will be consumed in equal amount (i.e., $p_i = p$ and $c_i = c \ \ \forall i$):

$$c = \frac{p^{-\sigma}}{P^{1-\sigma}} = f\left(\frac{\sigma - 1}{\sigma}\right),$$

given that $p = \frac{\sigma}{\sigma - 1}\beta_i$, and $P = \left(\int_0^n p^{1-\sigma} di\right)^{\frac{1}{1-\sigma}}$. As a consequence, exploiting $q_i = c_i = c$ and plugging the previous result into equation (6) the equilibrium wage is:

$$w = \frac{1}{\sigma}. \tag{7}$$

4 Consumption, production and education with two technologies

In this section, firms can improve their efficiency by adopting the *new* cost-reducing technology (recall that $\beta_n = \beta < \beta_o = 1$). However, as discussed in section 2.3, this requires specialized (skilled) labor. The amount of specialized labor in the economy, $L_n \in [0, 1]$, is the outcome of the education choices of all workers, whose decision reflects the net return to education (i.e., wage net of education costs).

Since firms producing with old and new technologies will offer different wages (i.e., w_o and w_n respectively), workers will only specialize in the new technology if this entails sufficient benefit. Workers are heterogeneous in their education costs x, and we also assume that these costs increase with the efficiency of the new technology (lower β) (see section 2.3).

Formally, workers will invest in education if and only if:

$$ln\left(w_n\right) + ln\left(1 - z\right) > ln\left(w_o\right). \tag{8}$$

Exploiting the fact that $z = (x - 1)/x$, we identify the marginal condition:

$$x^* = \frac{w_n}{w_o}, \tag{9}$$

such that all workers facing a smaller cost ($x \leq x^*$) invest in education, and all workers with higher costs ($x > x^*$) do not invest in education. Normalizing the total labor endowment to 1, the threshold in equation (9) yields

$$L_n = 1 - \int_{x^*}^{\infty} f(x)dx = F\left(x^*, \beta\right), \tag{10}$$

while $L_o = 1 - L_n$ represents the supply of unspecialized labor.

Varieties produced with the same technology are sold at the same price. Hence, we can write the price index as $P = \left(n_o p_o^{1-\sigma} + n_n p_n^{1-\sigma}\right)^{\frac{1}{1-\sigma}}$. Unspecialized workers will be employed by firms using the old technology and receive a wage w_o, whereas specialized workers receive a wage w_n. Using equations (4) and (5) and the price index, we get:

$$w_o = \frac{1}{\sigma\left(L_o + L_n\beta^{1-\sigma}\right)} \qquad \textit{and} \qquad w_n = \frac{1}{\sigma\left(L_o\beta^{\sigma-1} + L_n\right)}\ . \tag{11}$$

Therefore, the wage ratio is constant and solely determined by the efficiency of the new technology and the elasticity of substitution σ,

$$x^* = \frac{w_n}{w_o} = \beta^{1-\sigma}\ . \tag{12}$$

Please note that wages w_o and w_n are both endogenous and function of the labor supply of specialized and unspecialized workers. In our setting, the parameter β also determines how specialized labor supply responds to the wage ratio. In particular, given that $\frac{\partial F}{\partial \beta} > 0$, other things equal, new technologies that are only marginally more productive and therefore easier to learn induce larger shares of specialized workers.

The wage ratio determines how many firms will produce with the new technology. If L_n workers are employed using the new technology, the number of produced varieties is $n_o + n_n = \frac{L_o + L_n}{f}$.

The following proposition links the relative efficiency of the new technology to the share of specialized labor, and shows that this link is determined by the elasticity of substitution σ.

Proposition 1. *The share of specialized labor, L_n, can either increase or decrease with the relative efficiency of the new technology depending on the elasticity of substitution, σ. In particular, there exists a threshold value $\hat{\sigma}$ such that:*

(i) If $\sigma > \hat{\sigma}$, the share of specialized workers increases with the efficiency of the technology (i.e., decreases with β);

(ii) If $\sigma < \hat{\sigma}$, the share of specialized workers decreases with the efficiency of the technology (i.e., increases with β).

Proof. See Appendix A.1. □

Proposition 1 follows from the marginal effect of an increase in the technology efficiency (a decrease in β) on the volume of specialized labor L_n:

$$-\frac{\partial L_n}{\partial \beta} = -\frac{\partial F(x,\beta)}{\partial \beta} = \underbrace{\frac{dF\left(x,\beta\right)}{dx}\frac{\sigma-1}{\beta^{\sigma}}}_{\text{wage effect}} - \underbrace{\frac{dF\left(x,\beta\right)}{d\beta}}_{\text{learning effect}} \tag{13}$$

In particular, an increase in the technology efficiency (lower β) has two opposing effects.

On the one hand, a positive *wage effect* follows from the fact that a decrease in β creates a larger wage ratio, resulting in a larger share of workers wanting to invest in specialized education. Note that, for any given distribution of education costs, this positive *wage effect* is stronger when the products are less differentiated (higher σ).[10]

On the other hand, there also exists a negative *learning effect*, since the technology efficiency affects the distribution of the costs faced by workers, decreasing the incentive to invest in education and, therefore, the share of specialized workers.

The elasticity of substitution plays a fundamental role in determining which effect dominates. In fact, the *wage effect* dominates when the elasticity of substitution is sufficiently large (see Figure 1, top panel). The intuition is similar to that given by Melitz

[10]Notice that $\frac{dF(x,\lambda)}{dx}$ depends on the threshold x^*, which is increasing in σ.

(2003). As σ increases, firms producing with the new (more efficient) technology enjoy higher revenues due to the market share they are able to steal from less efficient firms. This allows them to pay higher wages relative to less efficient firms. This results in a larger wage ratio w_n/w_o, magnifying the positive wage effect as the return to education increases. However, when the elasticity of substitution is relatively small, the *learning effect* prevails, and technology adoption declines due to a shortage of specialized labor. (see Figure 1, bottom panel).

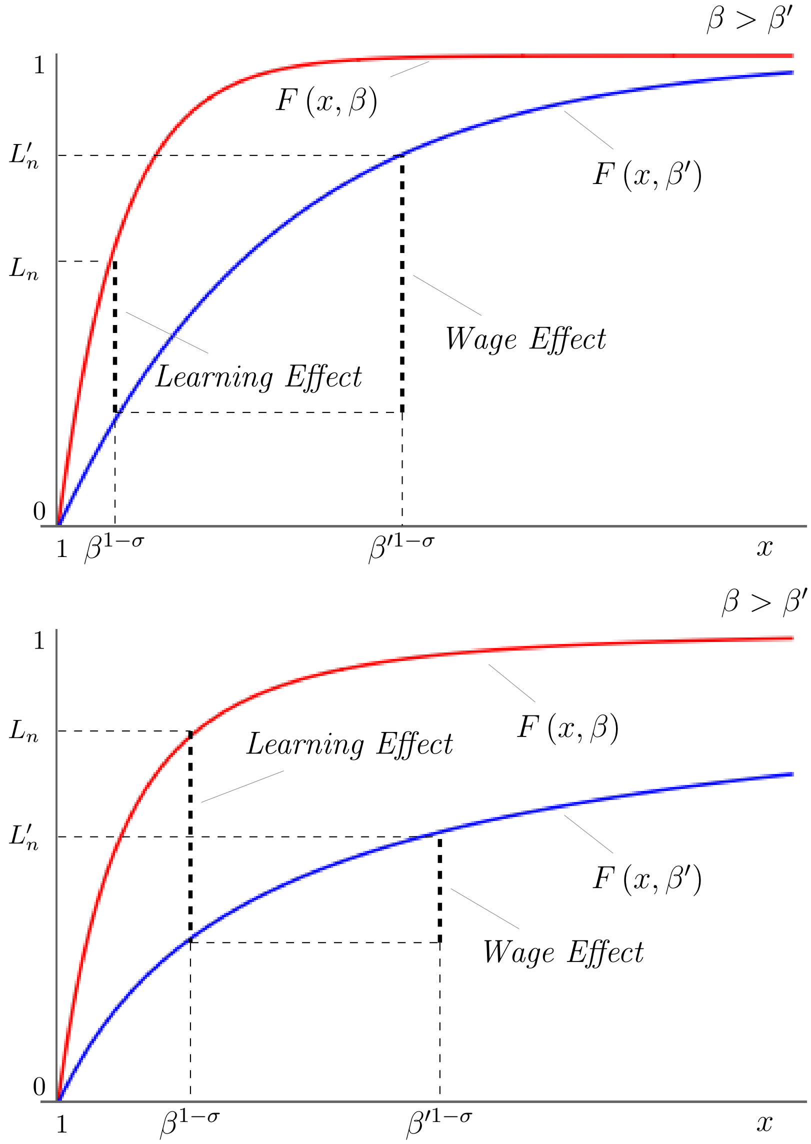

Figure 1: *Top Panel* – high σ: the wage effect dominates the learning effect. *Bottom Panel* – low σ: the learning effect dominates the wage effect.

The threshold value $\hat{\sigma}$ depends on the distribution of education costs. To illustrate the role of product differentiation, we consider two conventional distributions of education costs.

Pareto distribution. This distribution has often been used in previous literature, e.g., Delogu et al. 2018. In the *Pareto* distribution of the type

$$F(x;\lambda) = 1 - \left(\frac{1}{x}\right)^{\lambda}, \tag{14}$$

the parameter λ measures the relative size of the tails, with higher values of λ corresponding to a higher mass of workers with high education cost. To be consistent with our assumption in section 2.3, we relate the shape parameter λ to the efficiency of the technology as follows: $\lambda = \frac{\beta}{1-\beta}$, so that $\partial F(\cdot)/\partial\beta > 0$. We can conclude the following:

Corollary 1. *If education costs are Pareto distributed, a more efficient technology reduces the share of specialized workers.*

Proof. See Appendix A.2. □

Corollary 1 highlights the fact that with a Pareto distribution, the *learning effect* always offsets the *wage effect*. As we show in the appendix, this behavior can be explained by the fact that the wage effect is proportional to the learning effect, scaled by $\frac{(1-\beta)^2}{-\log(\beta)} < 1$.

Shifted exponential distribution. Let us consider an exponential distribution of the type:

$$F(x;\lambda) = 1 - e^{-\lambda(x-1)}. \tag{15}$$

Since the role of λ in the exponential and Pareto distributions has a similar interpretation, we can assume the same relationship between λ and β (i.e., $\lambda = \frac{\beta}{1-\beta}$). Compared to the case of the Pareto distribution, when the education costs are distributed according to a shifted exponential the learning effect does not seem as relevant due to the fast increase of the c.d.f.. In this way, a change in the wage ratio is more effective in increasing the share of specialized workers.

Corollary 2. *If education costs are distributed according to an Exponential distribution, an increase in production efficiency translates into more specialized labor if $\sigma > \hat{\sigma} = 2$ (less if $\sigma < 2$).*

Proof. See Appendix A.3. □

In the case of the *exponential distribution*, the positive wage effect prevails if products are less differentiated. When the elasticity of substitution is high enough ($\sigma > 2$), the *wage effect* prevails and a more efficient technology yields a higher return to education, increasing the supply of specialized labor.

To better grasp the impact of the distribution of education costs, Figure 2 depicts the inverse of the wage ratio w_o/w_n and the share of specialized workers, when $\sigma < 2$ (left Panel), and $\sigma > 2$ (right Panel). When education costs are Pareto distributed, σ has only a limited impact on the share of specialized labor at different levels of β. This share (L_n^{Par} as indicated in Figure 2) is always increasing in β. However, when education costs are exponentially distributed the share of specialized labor, L_n^{exp}, increases with β for low elasticities of substitution (left panel), while it decreases for high values of σ (right panel). When products are sufficiently differentiated (low σ), a more efficient technology induces less workers to invest in specialized education. This is because the positive demand effects induced by a more efficient technology are not enough to compensate for the increased specialization cost.[11]

[11] We do not show the case of $\sigma = 2$, in which L_n^{Exp} is represented by a flat horizontal line.

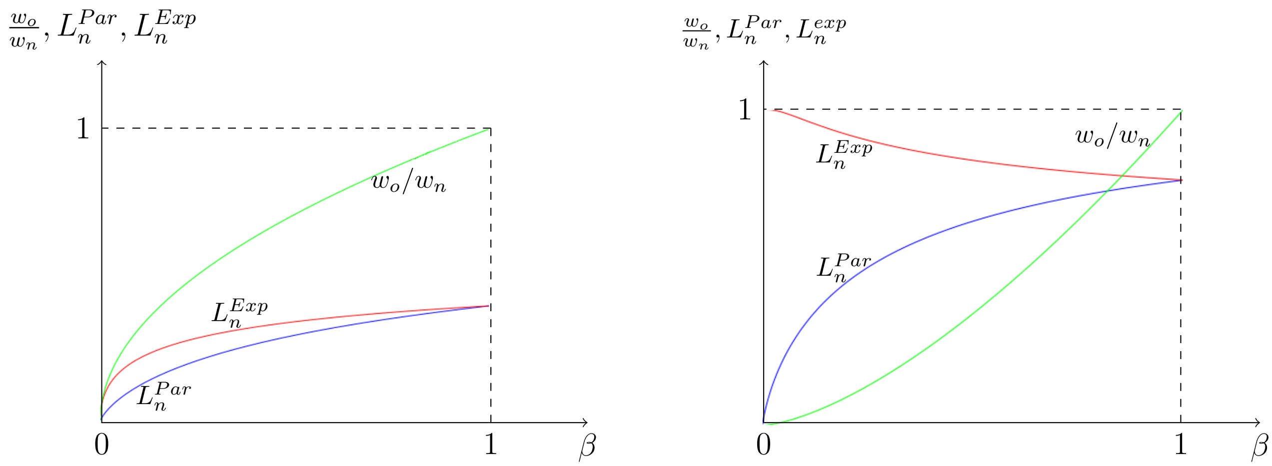

Figure 2: *Left Panel:* Wage ratio w_o/w_n, share of specialized workers under the Pareto distribution L_n^{Par} and under the Exponential distribution L_n^{Exp} with $\sigma < 2$. *Right Panel:* Wage ratio w_o/w_n, share of specialized workers under the Pareto distribution L_n^{Par} and under the Exponential distribution L_n^{Exp} with $\sigma > 2$.

5 Conclusions

Starting from the observation that firms often report shortages of skilled labor as a limit to technology adoption, this paper develops a tractable model linking education choices to technology diffusion. Employing a new technology often requires specialized labor, which can only be trained through costly education. Assuming that this cost increases with the potential improvements of new technologies, we link the efficiency of the new technology to the effort required to acquire the necessary skills.

This allows us to identify two opposing forces acting on education incentives, which determine the rate of technology adoption. On the one hand, a more efficient technology implies a larger wage ratio, encouraging skill accumulation (positive wage effect). On the other hand, since higher efficiency increases the average specialization cost, it also reduces the share of specialized workers (negative learning effect). When the learning effect dominates, labor shortages curb technology adoption. In line with empirical evidence, Beneito et al. (2015), our paper shows that the degree of differentiation is an important determinant of technology adoption. In particular, we show that the learning effect dominates when products are sufficiently differentiated.

Our findings suggest that in sectors where competition is low, more firms may fail to adopt more efficient technologies because high product differentiation compresses the wage premium, reducing incentives for specialization. This result is consistent with survey evidence reporting that shortages of specialized workers act as an obstacle to technology adoption. Better education policies, such as subsidizing specialization costs, can counter this adverse effect and foster the adoption of more efficient technologies.

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A Appendix

A.1 Proof of Proposition 1

Taking the total derivative of $F(x^*, \beta)$ we get the following,

$$dF(x^*, \beta) = \frac{\partial F(x^*, \beta)}{\partial x^*} dx^* + \frac{\partial F(x^*, \beta)}{\partial \beta} d\beta \ .$$

Exploiting the fact that

$$dx^* = (1 - \sigma)\, \beta^{-\sigma} d\beta$$

we have

$$dF = \left(-\frac{\partial F(x^*, \beta)}{\partial x^*} \frac{\sigma - 1}{\beta^{\sigma}} + \frac{\partial F(x^*, \beta)}{\partial \beta} \right) d\beta \ . \tag{A.1}$$

Therefore, the sign of $dF/d\beta$ depends on what is inside the brackets of equation A.1. Notice that

$$sign\left(\frac{\partial F(x^*, \beta)}{\partial x^*}\right) = sign\left(\frac{\partial F(x^*, \beta)}{\partial \beta}\right) > 0 \ .$$

Hence, $\frac{\partial F(x,\beta)}{\partial \beta} \geq 0$ if

$$\frac{\sigma - 1}{\beta^{\sigma}} \leq \frac{\frac{\partial F(x,\beta)}{d\beta}}{\frac{\partial F(x,\beta)}{\partial x}} \ . \tag{A.2}$$

The LHS of inequality (A.2) is monotonically increasing in σ. Therefore, there exists a threshold value $\hat{\sigma}$ such that condition (A.2) holds with equality and below which $\frac{\partial L_n}{\partial \beta} > 0$.

A.2 Proof of Corollary 1

Pareto distribution. Plugging equation (14) into equation (A.2) and considering that $\lambda = \frac{\beta}{1-\beta}$, equation (A.2) reduces to:

$$\sigma - 1 \leq \frac{\log\left(\beta^{\sigma-1}\right)}{\beta - 1}, \tag{A.3}$$

which is always verified when $\sigma > 1$.

A.3 Proof of Corollary 2

Exponential distribution. Taking equation (15) and using the fact that $\lambda = \frac{\beta}{1-\beta}$, we obtain:

$$\frac{\partial F(x,\lambda)}{\partial x} = \lambda e^{\lambda(-(x-1))} \tag{A.4}$$

and

$$\frac{\partial F(x,\lambda)}{\partial \lambda} = (1-x)\left(-e^{\lambda(-(x-1))}\right) \ . \tag{A.5}$$

Plugging into (A.2) equations (A.4) and (A.5) together with equation (9), we get:

$$\sigma - 1 \leq \frac{(\beta - \beta^{\sigma})}{\beta(1-\beta)} \ , \tag{A.6}$$

which is verified only if $\sigma < 2$.

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