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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 products are sufficiently differentiated.

1. Introduction

New technologies can significantly affect main economic aggregates through changes that usually begin in the industry supply. Technology adoption is essential for these changes to affect productivity and employment, as well as competition. Therefore, understanding the channels through which new technology is adopted has become increasingly relevant to anticipate their influence on firms operating in the international market.

Trade can influence technology development and adoption in several ways. For example, following a standard Heckscher–Ohlin argument, trade increases the demand for skill-intensive goods in countries that are relatively abundant in skilled labor, thus incentivizing the demand for such technologies and further inducing technological change. Also, in a framework with similar countries, Epifani and Gancia (2008) show that trade can positively affect the skill premium. Moreover, since Melitz (2003), it has been shown that trade has a selection effect, as more productive firms are those more successful in the international market. Accordingly, trade liberalization triggers faster technological adoption through the increased market incentive to incur the required costs. Finally, the last decades are characterized by a skill-biased technological change (Acemoglu, 2002; Goldin and Katz, 2010). Other contributions such as Thoenig and Verdier (2003) and Acemoglu (2003) highlight that trade complements technological motives in explaining this phenomenon.

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Although trade fosters technology adoption, 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 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 relative efficiency 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 for these predictions has 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 specialized 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 the same amount of output with less 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.[6] 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. 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 on 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.[7] 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 uncertainty 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 differences in technology-driven growth between the U.S. and Europe. However,

[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 digitalization.

[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 retaining or developing their workforce.

[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.

[6] This assumption is similar to that used in previous literature. See Section 2.3 for a detailed discussion.

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

they assume that individuals have heterogeneous abilities that are uniformly distributed across the population. Our paper shows that 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 sizeable effects on productivity. Our analysis can provide a complementary explanation, as it links the productivity gains from new technology to skills and specialization costs.

The paper is organized as follows. Section 2 describes the model, Section 3 analyzes technology adoption decisions and Section 4 concludes.

2. The model

We model a small open economy in which monopolistically competitive firms produce for foreign consumers.[8] 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.

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,

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

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, which both depend on the technology employed by the firm.[9] For simplicity, we consider two technologies (old and new) associated with marginal costs in terms of capital β_o and β_n, with $\beta_n < \beta_o$, with price defined in the international market and normalized to 1.[10]

Accordingly, the profit of firms employing old and new technologies are:

$$\pi_o = p_o \cdot q_o - (\beta_o \cdot q_o + w_o \cdot f) , \qquad \pi_n = p_n \cdot q_n - (\beta_n \cdot q_n + w_n \cdot f), \tag{2}$$

where q is the firm's output and p its unit price, while w is the wage. Each firm sets the price of its variety to maximize profits, while the aggregate wages determine the number of firms producing with the new technology in the market (free entry).

Throughout the analysis of Section 3, and without loss of generality, we normalize β_o to 1, so that $\beta_n = \beta \in (0, 1)$.[11]

2.3. Education decisions and technology efficiency

Workers are heterogeneous in their education effort, $x \in [1, \infty)$, which determines the disutility z of acquiring specialized education as follows: $z = (x-1)/x$.[12] 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 c.d.f. $F(x)$.

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

[9] This is similar to Ago et al. (2017). As Epifani and Gancia (2008) we assume extreme skill intensity. Firms producing with the new technology only employ specialized workers and while the others only unspecialized workers.

[10] Our model features a globalized economy in line with Klein and Ventura (2009), Kennan (2013) and Delogu et al. (2018). There is evidence that capital adjustments are rapid in open economies (see Ortega and Peri, 2009).

[11] This recalls (Elberfeld and Götz, 2002) in which firms incurring larger fixed cost access a more productive technology.

[12] To assign a utility cost to the effort x, we define the cost of specialization, z, as a convenient mapping associating a utility value to the required specialization effort of each worker ($z : X \to [0, 1]$).

Although the *new* technology has the advantage of reducing marginal costs, it requires firms to hire specialized labor L_n. It is clear that recent technologies are more productive than older ones, and that one can think about many new technologies that may be easier to learn (de-skilling technological change). However, as documented by Acemoglu (2002), the past several decades are characterized by a technological change that favors more specialized workers (skilling technological change). Something that has already been observed by Nelson and Phelps (1966), Nelson et al. (1967), and more recently again by Goldin and Katz (2010).[13] This reveals that the cost of adoption has increased with the efficiency of new technologies over the years, because of the additional educational efforts required to learn them.[14] This seems to be also consistent with recent empirical evidence that the availability of skilled labor is the main obstacle to technology adoption reported by firms.[15] Bartel and Lichtenberg (1987) and Bartel et al. (2007) provide additional empirical evidence. Bartel and Lichtenberg (1987) finds that highly educated workers have a comparative advantage in adopting new more efficient technologies given the amount of learning they require. Bartel et al. (2007) reports similar evidence focusing on the valve industry.

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. This assumption is similar to that of Jovanovic and Nyarko (1996), who analyze technology adoption and learning-by-doing in a dynamic framework.

3. Analysis

In this section, we analyze the model. We first focus on education decisions and then we analyze consumption and production. Recall that 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 labor.

Education decisions. 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:

$$ln\left(w_n\right) + ln(1-z) > ln\left(w_o\right). \tag{3}$$

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

$$x^* = \frac{w_n}{w_o}, \tag{4}$$

such that all workers facing a smaller cost ($x \le x^*$) 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 Eq. (4) yields

$$L_n = 1 - \int_{x^*}^{\infty} f(x)dx = F\left(x^*, \beta\right), \tag{5}$$

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

Production and consumption. The representative international consumer maximizes utility in Eq. (1) subject to a budget constraint ($1 = \int_0^n p_i c_i di$) by choosing the amount of each variety i taking into account its price, p_i.

Accordingly, the demand for varieties produced with technology of type i is:

$$c_i = \left(\frac{p_i}{P}\right)^{-\sigma}\frac{1}{P} \qquad with \quad i \in \{o, n\}, \tag{6}$$

where $P = \left(n_o p_o^{1-\sigma} + n_n p_n^{1-\sigma}\right)^{\frac{1}{1-\sigma}}$ is the price index. Each firm sets the price of the variety it produces to maximize its profit (Eq. (2)),

$$p_o = \frac{\sigma}{\sigma-1}, \qquad p_n = \frac{\sigma}{\sigma-1}\beta. \tag{7}$$

The optimal pricing strategy is a proportional mark-up on the marginal cost, independent of other firms' strategies. It is standard to interpret $\frac{1}{\sigma}$ as a measure of market power. Accordingly, an increase in σ reduces the market power of firms, because consumers are more willing to substitute varieties, which reduces their price. It follows from Eq. (7) that varieties produced with more advanced technologies will be sold at a lower price ($p_n < p_o$).

13 Nelson et al. (1967) wrote, *"The early ranks of computer programmers include a high proportion of Ph.D. mathematicians, today, high school graduates are being hired"*, Goldin and Katz (2010) report that more-educated individuals are more abundant in industries relying on newer and more efficient technologies. They also show that while this complementarity between technological advancements and skilled labor was not present in the past, it has been in place since 1980.

14 As Goldin and Katz (2010) wrote: *"The central idea concerning the role of technology in affecting inequality is that certain technologies are difficult for workers and consumers to master, at least initially"*.

15 See Elding and Morris (2018) and EIB Investment Survey 2021.

Finally, the free entry conditions of zero profits determine the labor market wages,

$$\pi_o = 0 \longrightarrow w_o = \frac{q_o(p_o - 1)}{f}. \tag{8}$$

$$\pi_n = 0 \longrightarrow w_n = \frac{q_n(p_n - \beta)}{f}. \tag{9}$$

Notice that relatively higher wages are paid by firms employing the more advanced technology. Using Eqs. (6) and (7) and the price index, we get:

$$w_o = \frac{1}{\sigma\left(L_o + L_n\beta^{1-\sigma}\right)} \qquad \textit{and} \qquad w_n = \frac{1}{\sigma\left(L_o\beta^{\sigma-1} + L_n\right)} . \tag{10}$$

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

$$x^* = \frac{w_n}{w_o} = \beta^{1-\sigma} . \tag{11}$$

Please note that wages w_o and w_n are both endogenous and function of the labor supply of specialized and unspecialized workers.[16] 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 induce larger shares of specialized workers.

The wage ratio contributes to determining 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.2. □

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:

$$-\frac{dL_n}{d\beta} = -\frac{dF(x,\beta)}{d\beta} = \underbrace{\frac{\partial F(x,\beta)}{\partial x}\frac{\sigma-1}{\beta^\sigma}}_{\text{wage effect}} - \underbrace{\frac{\partial F(x,\beta)}{\partial \beta}}_{\text{learning effect}} \tag{12}$$

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).[17] 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. The top panel in Fig. 1 shows two cumulative distribution functions of worker's type x and the corresponding shares of specialized labor L_n. The blue curve is associated with a slightly more efficient technology (lower β). Therefore, the graph shows what would happen to the share of specialized labor L_n if following an increase in the efficiency of the new technology (from red to blue) the wage effect was to dominate. As one can see, while due to the learning effect it becomes more costly to acquire the skills necessary for the new (blue) technology, still more workers find specialization convenient due to the wage effect. The marginal worker shifts to the right and the share of specialized labor increases from L_n to L_n'. The intuition is similar to that given by Melitz (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 Fig. 1, bottom panel).

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.

[16] Assuming different fixed costs in terms of labor for old and new technology (say $f_o \neq f_n$) would not change the paper results as the wage ratio would simply equal $\frac{f_o}{f_n}\beta^{1-\sigma}$. We show in Appendix A.1 that generalizing the cost function in a way similar to Epifani and Gancia (2008) would not change qualitatively our results.

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

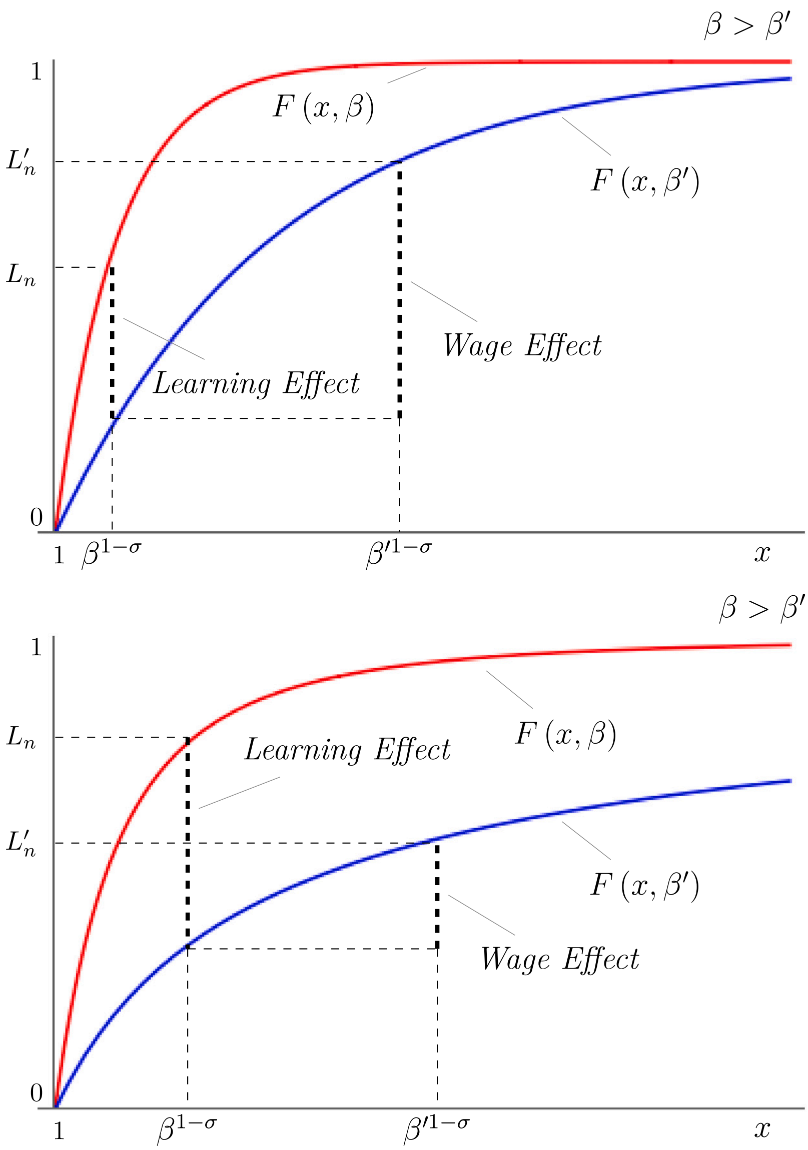

Fig. 1. *Top Panel* – high σ: the wage effect dominates the learning effect. *Bottom Panel* – low σ: the learning effect dominates the wage effect.

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

$$F(x;\lambda) = 1 - \left(\frac{1}{x}\right)^{\lambda}, \tag{13}$$

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 $\lambda = \frac{\beta}{1-\beta}$ and education costs are Pareto distributed, a more efficient technology reduces the share of specialized workers.*

Proof. See Appendix A.3. □

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 $\frac{(1-\beta)^2}{-\log(\beta)} < 1$.

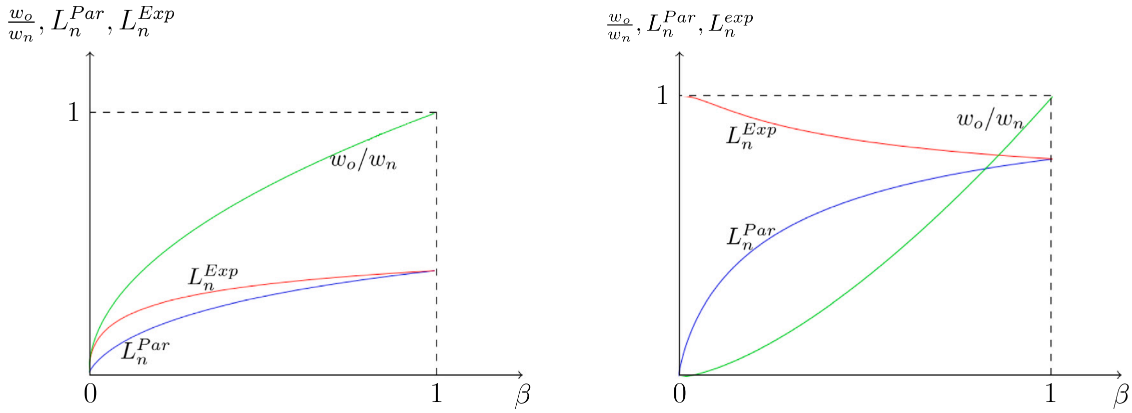

Fig. 2. *Left Panel:* Wage ratio w_o/w_n, share of specialized workers under the Pareto distribution L_n^{Par} and under the Exponential distribution L_n^{Exp} with $\sigma < 2$. *Right Panel:* Wage ratio w_o/w_n, share of specialized workers under the Pareto distribution L_n^{Par} and under the Exponential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

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

$$F(x;\lambda) = 1 - e^{-\lambda(x-1)}. \tag{14}$$

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 $\lambda = \frac{\beta}{1-\beta}$ and 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.4. □

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, Fig. 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 Fig. 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 fewer 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.[18]

Welfare and policy considerations. In our model, total welfare is determined by the population of workers and international consumers. This is because the free entry condition guarantees that all operating profits generated by firms are transferred to workers in terms of wages and, hence, utility.[19]

Workers can be split into two categories. Specialized workers (people with $x < \hat{x}^*$, a share L_n) receive a wage equal to w_n but face the education cost, while unspecialized (a share $L_o = 1 - L_n$) receive a wage w_o. After some computations that we provide in Appendix A.5, we obtain:

$$U_w(x^*) = \ln(w_o(x^*)) + F(x^*)\left(\ln\left(\frac{w_n(x^*)}{w_o(x^*)}\right) - \ln(x^*)\right) + \int_1^{x^*} \frac{F(x)}{x}dx \tag{15}$$

Therefore, the threshold x^* determining the share of specialized workers has ambiguous effects on overall workers' utility, which ultimately depend on the distribution of workers.

For international consumers, on the other hand, two remarks are in order. First, the consumption of a given variety is decreasing in its price (see Eq. (6)). Varieties produced with the old technology are more expensive which has a lower marginal cost,

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

[19] Note that the full pass-through of operating profit to wages fosters technology adoption. Hence, with limited profit pass-through, there would be less technology adoption given the reduced wage effect.

$p_o = \frac{\sigma}{\sigma-1} > \frac{\beta\sigma}{\sigma-1} = p_n$. This implies that varieties produced with the new technology are consumed more than those produced with the old technology (i.e., $c_0 < c_n$). Second, the number of varieties produced with the new or old technology is proportional to the share of firms employing specialized or unspecialized workers respectively, i.e., $n_n = \frac{L_n(x^*)}{f}$ and $n_o = \frac{1-L_n(x^*)}{f}$. With these two remarks in mind, the consumers' utility can be expressed as follows:

$$U_c(x^*) = \left(n_0(c_o)^{\frac{\sigma-1}{\sigma}} + n_n(c_n)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} = \left(\frac{1-L_n(x^*)}{f}(c_o)^{\frac{\sigma-1}{\sigma}} + \frac{L_n(x^*)}{f}(c_n)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} . \tag{16}$$

Therefore, given that $c_o < c_n$, it is clear that $\frac{\partial U}{\partial L_n(x^*)} > 0$, i.e., the utility of international consumers increases with the share of specialized workers. Overall, we can conclude that the main determinant of welfare in our setup is the adoption of a new efficient technology, which increases the utility of consumers and in turns depends on the availability of specialized labor.[20]

In summary, while the share of specialized workers improves the welfare of international consumers, it has ambiguous effects on the overall utility of workers.

Subsidy to education. This paragraph discusses if a tax policy aimed at improving education among workers can benefit the share of specialized labor as well as total welfare. To this end, we consider the introduction of a wage tax on all workers, $t \in (0,1)$, to finance an education subsidy $s \in (0,1)$. This policy would certainly affect the net return to education and so the incentive to specialization. Formally, after the introduction of this policy, workers will invest in education if and only if:

$$\ln\left(w_n\left(1-t'\right)\right) + \ln(1-z) > \ln\left(w_o(1-t)\right)$$

where $t'(s) < t$ represents the effective tax rate ultimately paid by specialized workers (i.e., wage tax net of the subsidy). This effective tax rate is a decreasing function of the subsidy s.[21]

Now, recalling that $z = (x-1)/x$, we can identify a new marginal condition:

$$x^{**} = \frac{w_n}{w_o}\left(\frac{1-t'}{1-t}\right) \equiv x^*\left(\frac{1-t'}{1-t}\right) , \tag{17}$$

such that all workers facing a smaller cost ($x \le x^{**}$) invest in education, and all workers with higher costs ($x > x^{**}$) do not invest in education. The term $\left(\frac{1-t'}{1-t}\right)$ in Eq. (17) represents the effect of the policy on the education incentive. This effect is positive, since $\left(\frac{1-t'}{1-t}\right) > 1$ given that $t' < t$. It follows that $x^{**} > x^* = \frac{w_n}{w_o}$, indicating that the introduction of this type of policy increases the number of specialized workers, i.e., $L_n^{**} = F(x^{**},\lambda) > F(x^*,\lambda) = L_n^*$. However, the impact of the education subsidy on total welfare is ambiguous as this policy has re-distributive effects. While the utility of international consumers increases that of workers may decrease. Therefore, an optimal policy would depend on the relative importance that a government assigns to international trade versus the internal labor market as well as the cost of implementing the policy.

4. Conclusions

Starting from the observation that firms often report shortages of specialized 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 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 can counter this adverse effect and foster the adoption of more efficient technologies.

Future research may relate our mechanism to the one developed in Cervellati et al. (2018) who show that adopting new technologies in developing countries requires both openness to trade and democratization. Trade openness alone may fail to foster technology adoption if that hurts the interests of the elite in power. Therefore, democratization can counter this adverse effect. We

[20] The other important element is the elasticity of substitution which, however, has ambiguous effects for workers, as it increases the pool of specialized workers, but decreases their wage, as we show in Appendix A.5.

[21] It is easy to show that if all tax revenues are used to subsidize specialized workers, then these workers will not pay any taxes on their wages. To see this, consider the government binding budget, $w_n L_n(t-s) + w_o L_o t = 0$, equivalent to setting $t' = t - s$, meaning all collected taxes are transferred to specialized workers. Then, $s = t\left(1 + \frac{L_o}{L_n}\frac{w_o}{w_n}\right) \ge t$ and $t' \le 0$, given that $\frac{L_o}{L_n}\frac{w_o}{w_n} \ge 0$. Note that a full transfer of the wage tax is not necessary for the policy to foster education.

show that market power, which may also have an influence on the interest of the elite in power, has a direct effect on technology adoption through education incentives. Empirically, one can exploit time-varying measures of market power provided by De Loecker and Eeckhout (2021) to evaluate the effect that market power may have on technology adoption and democratization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

A.1. General cost function

In this appendix, we consider a more general way to extend the cost function of our model by allowing firms to use both specialized and unspecialized workers, with different degree of substitutability that depends on the production technology. In particular, the fixed cost is assumed to be a Cobb–Douglas function of specialized and unspecialized labor wages (see also Epifani and Gancia, 2008). Therefore, the total cost functions of firms producing with old and new technology become:

$$TC_o = q_o + w_n^{\varepsilon} w_o^{1-\varepsilon} f,$$
$$TC_n = \beta \cdot q_n + w_n^{\gamma} w_o^{1-\gamma} f \ ,$$

where ε and γ represent the wage-bill share of specialized workers for firms producing with the old and new technology respectively. We further assume that $\gamma > \varepsilon$ to capture that producing with the new technology requires a higher share of specialized labor. Taking advantage of the free-entry condition and profit maximization behavior, we determine the wage ratio and the marginal condition $\tilde{x}$ such that all workers facing a smaller cost ($x \leq \tilde{x}$) invest in education:

$$\tilde{x} = \beta^{\frac{1-\sigma}{\gamma-\varepsilon}} .$$

Given that $\gamma > \varepsilon$, it follows that the claims of Proposition 1 are confirmed in this more general setup.

A.2. 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 Eq. (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.3. Proof of Corollary 1

Pareto distribution. Plugging Eq. (13) into Eq. (A.2) and considering that $\lambda = \frac{\beta}{1-\beta}$, Eq. (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.4. Proof of Corollary 2

Exponential distribution. Taking Eq. (14) 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) Eqs. (A.4) and (A.5) together with Eq. (4), we get:

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

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

A.5. Derivation of total workers utility in Corollary 2

Worker's utility. Here below we compute the overall utility of workers:

$$\begin{aligned}
U_w(w_o, w_n) &= \int_1^{x^*} \left[\ln(w_n) + \ln(1-z)\right] f(x)dx + \int_{x^*}^{\infty} \ln(w_o) f(x)dx \\
&= \ln(w_n)\int_1^{x^*} f(x)dx + \int_1^{x^*} \ln(1/x) f(x)dx + \ln(w_o)\int_{x^*}^{\infty} f(x)dx \\
&= \ln(w_n)F(x^*) + \int_1^{x^*} \ln(1/x) f(x)dx + \ln(w_o)\left[1 - F(x^*)\right] \\
&= F(x^*)\left[\ln(w_n) - \ln(w_o)\right] + \ln(w_o) + \int_1^{x^*} \ln(1/x) f(x)dx \\
&= F(x^*)\ln\left(\frac{w_n}{w_o}\right) + \ln(w_o) - \int_1^{x^*} \ln(x) f(x)dx \\
&= F(x^*)\ln\left(\frac{w_n}{w_o}\right) + \ln(w_o) - \left[\ln(x)\, F(x)\right]_1^{x^*} + \int_1^{x^*} \frac{F(x)}{x}dx \\
&= F(x^*)\ln\left(\frac{w_n}{w_o}\right) + \ln(w_o) - \left[\ln\left(x^*\right) F(x^*)\right] + \int_1^{x^*} \frac{F(x)}{x}dx \\
&= \ln(w_o) + F(x^*)\left(\ln\left(\frac{w_n}{w_o}\right) - \ln(x^*)\right) + \int_1^{x^*} \frac{F(x)}{x}dx = U_w(x^*)
\end{aligned}$$

The threshold x^* has clearly ambiguous effects on the utility of workers, as does the elasticity of substitution σ. Using the equilibrium relationship between wages $\frac{w_n}{w_o} = \beta^{1-\sigma}$, with some manipulation we can rewrite the utility as,

$$U(x^*) = \ln(w_o(x^*)) + F(x^*, \beta)(\sigma - 1)\ln\left(\frac{1}{\beta}\right) + \int_1^{x^*} \ln\left(\frac{1}{x}\right) dF(x) \ .$$

This allows to better study the effect of σ on overall workers' utility, which is also ambiguous. While the second term of $U(x^*)$ is increasing in σ, w_o is not. Recalling Eq. (10),

$$w_o = \frac{\beta^{\sigma-1}}{\sigma\left[(1-L_n)\beta^{\sigma-1} + L_n\right]} \ ,$$

notice that the numerator of w_o decreases with σ since $\beta \in (0,1)$. Also, since $L_n = F(x^*) = F(\beta^{1-\sigma})$, the denominator of w_o increases with σ. Therefore, we can conclude that w_o decreases with σ.

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