How Susceptible are Skills to Obsolescence? A Task-Based Perspective of Human Capital Depreciation

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Abstract

This article investigates the link between human capital depreciation and job tasks, with an emphasis on potential differences between education levels. Using data from the German Socio-Economic Panel, fixed effects panel regression is applied to estimate an extended Mincer equation based on Neumann and Weiss's model. Human capital gained from higher education levels depreciates at a faster rate than other human capital. The depreciation rate is also higher for specific skills compared to general skills. Moreover, the productivity-enhancing value of education diminishes more rapidly in jobs with a high share of non-routine interactive, non-routine manual, and routine cognitive tasks. These jobs are characterized by greater technology complementarity or more frequent changes in core-skill or technology-skill requirements.

The presented results point to the urgency of elaborating combined labor market and educational and lifelong learning policies to counteract the depreciation of skills. Education should focus on equipping workers with more general skills in all education levels and adapting educational programs to take into account the rapid upgrade of production technologies and changing competency requirements.

Keywords: education; human capital; depreciation; skills; obsolescence; tasks; technological change; earnings

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Introduction

Educational organizations train workers to perform various sets of tasks in accordance with market realities. At the same time, with the proliferation of information and communication technologies (ICT) and robotics, the content of work processes is changing: machines are taking on increasingly more routine operations, while new tasks for human workers arise. As a result, qualification requirements are changing, with some of the previously acquired competencies becoming irrelevant for the labour market. This process is called human capital depreciation. If previously it mainly affected personnel employed in knowledge-intensive sectors, with the accelerated technological development this trend is becoming more broad. The ongoing digital transformation is impacting an increasing number of occupations. Relevant solutions complement or replace human skills, leading to their obsolescence. First of all, this affects jobs involving complex cognitive, interactive, and analytical tasks, where the active use of technologies complements human workers. Since workers' skills quickly become obsolete, the economic value of human capital decreases accordingly. To remain competitive, workers need to improve their skills or acquire new professions. Technological and organizational changes will obviously accelerate and affect all areas of the economy, while the risk of skill depreciation will increase. This challenge must be met and appropriate policy action taken.

Despite the stable and long-term nature of the observed effects, the topic of knowledge depreciation in the context of technological change remains poorly understood. Backes-Gellner and Janssen (2009) describe the different ways in which competencies become obsolete, pointing to the need to take into account the specific features of work tasks as a determinant of this process. However, their results are limited because they do not consider the differences in human capital depreciation depending on the level of education.

In an attempt to fill the current gap, we aim to find out how changes in the nature of work tasks affect human capital depreciation at different levels. To the best of our knowledge, this is the first study that takes into account these aspects, distinguishing between different human capital types and work task groups. Accounting for differences in competency obsolescence depending on specific features of work tasks deepens our understanding of human capital depreciation models. More effective labor market and education policies can be shaped on this basis, which is critically important to helping the workforce adapt to the changing context.

Literature Review and Theoretical Framework

Skills depreciation

The human capital concept emerged in academic discourse decades ago (Becker, 1964; Mincer, 1974; Rosen, 1975). It comprises knowledge and skills acquired both over the course of formal education at educational organizations and during practical work. Human assets' current economic value is reflected by the remuneration workers receive and by their performance indicators. As with any other type of capital, professional qualifications can depreciate over time in two dimensions: technical and economic ones (Becker, 1964; Arrazola, Hevia, 2004; De Grip, Van Loo, 2002; Neuman, Weiss, 1995). The first is caused by internal factors such as workers' age, or insufficient application of their skills. The second involves a decrease in the market value of knowledge and skills due to changes in the economic environment, which is why it is often called external depreciation. The focus of our analysis is on the economic aspect.

Innovation-based development and the growth of high-technology industries led to labor substitution, creating a serious challenge for the "established" qualifications. With the development of labor-substituting technologies capable of performing repetitive production operations, such effects are becoming increasingly more pronounced.

Measuring competence depreciation

Empirical studies focused on the quantitative aspects of human capital obsolescence remain sporadic, while their methodological approaches are less than universal. A particularly broad range of models were applied for these purposes in early studies. The analysis of the relationship between workers' earnings, age, and experience revealed that competencies of workers with secondary education become obsolete faster than those of university degrees (Rosen, 1975). The qualifications of women with tertiary education depreciate at a particularly high rate (Mincer, Ofek, 1982). A number of experts believe the level of education does not play a decisive role here (Carliner, 1982; Holtmann, 1972). The age-earnings relationship was explored in more detail for such aspects as lifecycle investment models (Becker, 1964; Haley, 1976; Heckman, 1976; Johnson, Hebein, 1974) or interruptions in women's work (Mincer, Ofek, 1982). However, the above studies do not distinguish between internal and external depreciation. Only a single general indicator is taken into account: technical obsolescence of human capital due to insufficient use of skills or advanced age (De Grip, 2006; De Grip, Van Loo, 2002).

Currently, human capital depreciation is measured either directly or by using indirect indicators. Internal and external depreciation were first distinguished by (Neuman, Weiss, 1995). Human capital depreciation is measured indirectly through, e.g., the ratio of education to potential experience, and its impact on earnings (Mincer, 1974). The relationship of the "education" and "experience" variables is estimated based on the assumption that the economic value of knowledge and skills decreases depending on the length of time between the end of formal education and potential entry onto the labor market. The advantage of an indirect approach is that it captures the decline in productivity through earnings, which is the main problem in most countries (De Grip, 2006). It was established that negative effects on earnings in relation to the level of education and work experience are more pronounced in high-technology sectors where workers tend to have more advanced qualifications (Neuman, Weiss, 1995).

An improved version of this model was applied to examine the Spanish labor market (Murillo, 2011). The education depreciation rate was estimated at 0.7% in 1995 and 0.4% in 2002 (this indicator value grows along with the education level), and the experience depreciation at 3.8% and 1.8%, respectively. Calculations based on the extended earnings equation (Mincer, 1974) showed that the skill obsolescence rate was higher for workers whose jobs involved knowledge-based tasks, rather than experience-based ones (Backes-Gellne, Janssen, 2009).

An analysis of sectoral differences in human capital depreciation in OECD countries in 1980-2005 revealed fluctuations in the range from 1% to 6%, with this indicator value being higher in the sectors requiring high level of skills, regardless of the use of technology (Lentini, Gimenez, 2019). The knowledge depreciation rate increases with higher qualifications and reaches maximum values in high-technology industries (Ramirez, 2002). Mathematical modeling based on direct estimates showed that the human capital depreciation rate in the UK and the Netherlands was at 11%-17% (Groot 1998), and at 1.2%-1.5% in Spain, depending on the sector and the duration of unemployment (Arrazola, Hevia, 2004). The case of Switzerland (Weber, 2014) shows that specialized skills depreciate faster (0.9%-1.0%) than general ones (0.6%-0.7%). The variation in depreciation levels is most likely due to differences in measurement techniques, observation periods, and source data arrays. It was established that the competency obsolescence depends on their type, but not enough attention was paid to the role of the technological development factor that determines the state of affairs in most of the leading countries. Competency obsolescence was linked to work task types (knowledge- or experience-based ones) (Backes-Gellner, Janssen 2009), but the depreciation of formal training was not taken into account. Accordingly, the obtained results are poorly compatible and of little use for evaluating modern educational systems. In other studies, specific features of this loss of relevance in different professional segments was addressed only indirectly (Weber, 2014; Lentini, Gimenez, 2019).

The technological potential of labor substitution differs for different work task types, so it can be assumed that human capital obsolescence rates vary depending on the functional portfolio of a particular profession. To test this assumption and compare the results with the findings of previous studies, we focused both on work tasks (according to the classification described in the job polarization literature) and education depreciation.

Hypotheses

The above literature review allows one to suggest a number of hypotheses and clarify the role of work tasks in human capital depreciation. As was noted, it comprises two aspects: education and experience, but the "reserves" of each are subject to depreciation - which, together with investments, determine the current human capital value. Its depreciation rate depends on the category of personnel. The depreciation rate classifications proposed in previous studies (Murillo, 2011; Neuman, Weiss, 1995) are provisional and must be revised. In our opinion, the economic obsolescence of human capital caused by changes in the external context does not affect everyone equally, but depends on personal skills (basic and specialized) and the type of tasks performed. Core competencies are universal in nature, typically acquired over the course of general secondary or tertiary education and remain relevant in the long term even as the economic landscape changes. In turn, specialized skills are developed in the course of secondary vocational education and training (VET) or higher vocational education and training (HVET). They are based on the latest knowledge and focused on making use of particular technologies. However, the accelerating substitution of some production processes with others leads to a rapid depreciation of such qualifications. Accordingly, the following hypotheses are suggested:

H1a. *The higher the level of workers' education, the higher the rate of their skill depreciation.*

H1b. *The competencies of workers with higher and secondary vocational education depreciate more rapidly than those of workers with general education.*

The next group of hypotheses concerns the relationship between work tasks and skill obsolescence. Any profession comprises a set of tasks which cannot be performed without appropriate training (Rodrigues et al., 2021). In other words, competencies are determined by the nature of the job. Technological development leads to changes in work tasks and in competency requirements, which in turn results in obsolescence of the latter. Manual or repetitive tasks are gradually transferred to machines (Autor, Dorn, 2013; Autor, Handel, 2013; Frey, Osborne, 2017). Cognitive, analytical, or interactive tasks need more advanced human capital, often enhanced by technology. Occupations with a high share of non-routine operations include, e.g., financiers or programmers. However, specialized skills acquired during formal education are intended for the use of technologies relevant at the time, and as some production processes are replaced by others these skills depreciate. Accordingly, the demand for such workers frequently changes, which accelerates human capital depreciation. In turn, professions with a high share of manual operations tend to be less dependent on technology, so the human capital obtained through education remains valuable even in the context of ongoing digital transformation. This applies, e.g., to construction and food industry workers (Muro et al., 2017), for whom the rate of knowledge depreciation will be lower.

H2a. *The depreciation rate is higher for occupations with a significant share of interactive, analytical, and cognitive tasks which rely on technology.*

Our next assumption is that the rate of human capital depreciation depends on the scale of changes in technology application. Machines perform an increasingly broad range of tasks, gradually covering non-routine operations which previously remained the prerogative of people. Therefore in the course of technological development "non-routine" professions are more likely to require new skills, which will accelerate human capital depreciation.

H2b. *The more rapidly the technological upgrading of jobs occurs, the higher the depreciation rate of relevant competencies becomes.*

Data and Methodology

We estimated the depreciation rate and the factors affecting it using the German Socio-Economic Panel[1] for 1984-2017. It was possible to establish links between control variables (education, wages, etc.) and workers' professional characteristics. The human capital depreciation rate was calculated using an extended earnings function (Neuman, Weiss 1995; Mincer, Ofek 1982), which allowed for analyzing the impact of education on wages that decline over time. The education-specific depreciation is indirectly estimated by equation (1) as the relationship between tertiary education and work experience (the period of time elapsed since the completion of formal education *(Edu_i X $pexper_{it}$)*. The β2 coefficient indicates how skill obsolescence affects earnings.

$$\ln w_{it} = \beta_0 + \beta_1 Edu_i + \beta_2 (Edu_i \times pexper_{it}) + \beta_3 pexper_{it} + \beta_4 pexper_{it}^{\,2} + X_{it} + \varepsilon_{it} \qquad (1)$$

The use of a panel fixed effects estimation with cluster robust standard errors allowed the authors to take into account the autocorrelation and heteroscedasticity of the error terms. Controls for personal or job-related characteristics were applied stepwise.

To test the relationship between skill obsolescence and work task types, a categorical variable was constructed based on the German classification of occupations (KldB, 1992). In accordance with the method proposed in (Dengler et al., 2014), each occupa-

[1] SOEP v34i (doi: 10.5684/soep.v34i). https://www.diw.de/sixcms/detail.php?id=diw_01.c.742267.en, accessed 07.11.2021.

tion was assigned one predominant work task type. Based on the classifications presented in (Spitz-Oener, 2006; Autor et al., 2003), we distinguish between non-routine (interactive, analytical, manual) and routine (cognitive, manual) work tasks.[2]

The categorical variable *tasks* was used to distinguish between different work task types, first added to equation (1) to take into account the possible relationship with earnings. Subsequent calculations of equation (1) for each task group allowed us to determine how the depreciation rate varies for different work task types. The main variables are presented in Table 1.

Findings

Calculations based on various specifications of fixed effect panel regression are summarized in Table 2. In the preferred specification (column 4), the coefficient of the interaction term for all levels of education (except secondary) has a negative value, which indicates human capital depreciation.

The annual depreciation rate is lowest for workers with VET degrees (1.1%), followed by university degree holders (1.2%); the highest value was established for workers with higher VET (1.4%). Our observations are consistent with previous publications (Lentini, Gimenez, 2019; Neuman, Weiss, 1995), confirming the significant vulnerability of skills acquired over the course of higher education. In support of the findings of (Weber, 2014), it was also found that competencies acquired through VET (VET versus general secondary school and higher VET versus university) depreciate more rapidly. This implies the limited applicability of specialized human capital for other work tasks, and its depreciation when the economic context changes. Compared to other studies (Murillo, 2011), our depreciation rate calculated for each additional year of potential experience is relatively low (0.01%). A possible explanation is the time when our analysis was conducted: previous studies have noted a declining experience depreciation trend.

According to the regression results for the dominant work task categories (Table 3), the depreciation rate varies depending on the education and work task type, which empirically confirms the importance of both of these factors for competency obsolescence. Skills required to perform non-routine interactive, specific manual, and generic cognitive tasks are subject to a faster decline in relevance. The highest annual depreciation rate was found for non-routine interactive tasks: 2.0% for workers with tertiary education and 1.9% for workers with higher VET. Specialized skills of workers with higher VET become obsolete even faster (2.3%), and those of workers who mainly perform non-routine analytical tasks, on the contrary, depreciate at half that rate. Furthermore, the value of experience increases in relation to tasks with a higher level of depreciation (as indicated by the potential experience variable *pexper*).

To better understand the differences in depreciation rates, we have built predictive earnings-experience profiles for different types of tasks based on the results of Model Specification 5. Figure 1 shows that earning profiles significantly vary by task types and education levels. Earnings, including education premiums, tend to be lower for those performing manual tasks and higher for analytical, interactive, and cognitive ones. Towards the end of their careers, earnings of workers with VET will exceed those of workers with higher VET. As to non-routine manual tasks, VET and higher VET provide more significant income than general tertiary education. In addition, wages of secondary school graduates quickly peak and for a certain period of time exceed those of workers with VET and higher VET, but then rapidly lose ground. Despite reduced educational qualifications, at the beginning of one's career differences in depreciation levels in some cases can offset the difference in earnings. Therefore even university graduates need to constantly update their knowledge to maintain the value of their human capital.

A detailed analysis of occupations with a high share of interactive or cognitive tasks indicates that the use of technologies by such workers changes significantly. They widely apply supplementary digital solutions, primarily to perform cognitive and analytical tasks, while the rate of such technologies' evolution remains moderate (Table 4). Perhaps this explains the increased level of skill depreciation for workers who carry out such tasks. On the contrary, with non-routine manual work tasks, the use of technology increases dramatically. For example, they make up the core of construction, hotel, catering, and logistics occupations. In 2001 digital technologies were rarely applied for these purposes

[2] Data on job-related technology use comes from (Muro et al., 2017) who provide information on the use of technology for 545 occupations between 2001 and 2016.

Table 1. **Descriptive Statistics (full-time workers > 30 hours/week)**

Variable		Observations	Mean	Std. Dev.	Min	Max
Earnings (deflated base year 2015)						
lwage15	Log gross hourly wages	266,234	2.546	0.654	-0.728	5.330
Education level (base group: only secondary education)						
2	VET	488,577	0.512	0.500	0	1
3	Higher VET	488,577	0.072	0.259	0	1
4	High School (Abitur)	488,577	0.083	0.276	0	1
5	University	488,577	0.193	0.395	0	1
Potential experience (years)						
pexper	age - years in education	510,724	35.479	17.800	1	93
Tasks						
1	Non-routine analytical	266,537	0.233	0.423	0	1
2	Non-routine interactive	266,537	0.087	0.281	0	1
3	Non-routine manual	266,537	0.175	0.380	0	1
4	Routine cognitive	266,537	0.326	0.469	0	1
5	Routine manual	266,537	0.180	0.384	0	1

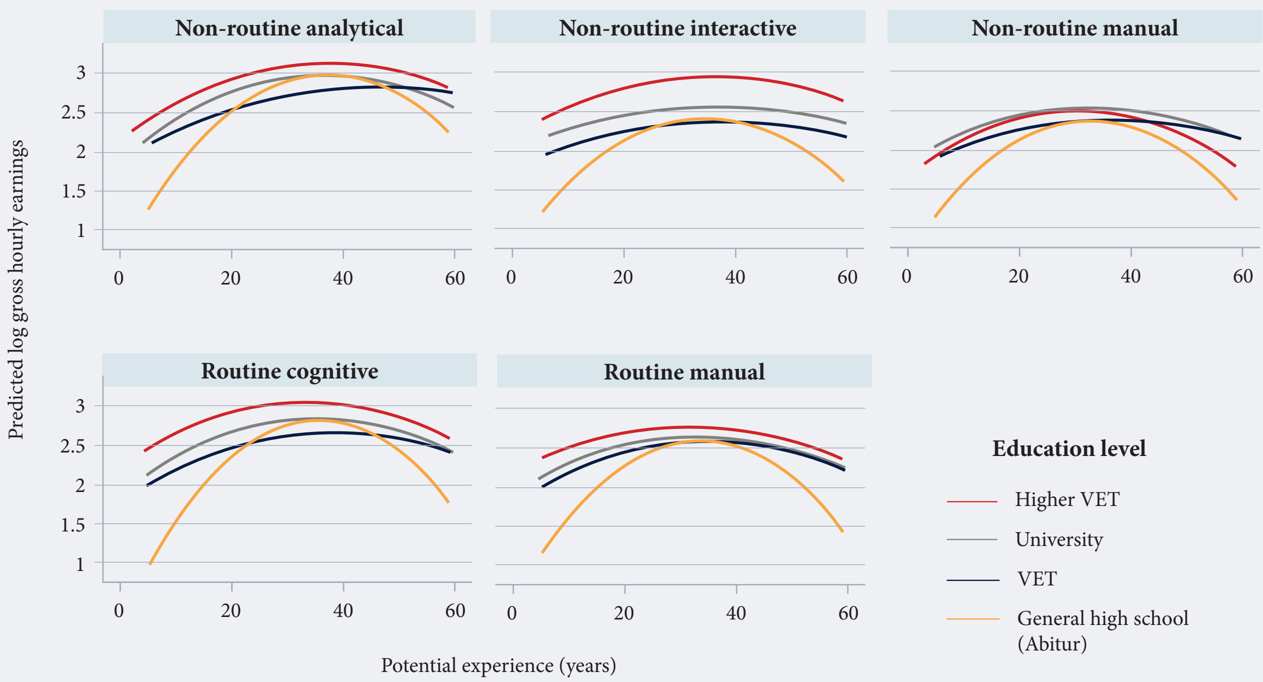
Source: composed by the authors using SOEP v34i. https://www.diw.de/sixcms/detail.php?id=diw_01.c.742267.en, accessed 07.11.2021.

(Muro et al., 2017), but by 2016, their use has doubled, accelerating competency depreciation. Thus, though the average skill obsolescence rate for the entire period is moderate, in recent years the pace of this process has increased. Compared to other professions, the use of technology here remains relatively low, but more significant changes can lead to increased competency depreciation.

Conclusion

Advances in technology development are changing the employment sphere and skill requirements, making human capital acquired through formal education obsolete. Digitalization is radically transforming the nature of work tasks and the demand for competencies, which creates new opportunities for some workers and risks for others. A deeper

Figure 1. **Predicted Earnings–Experience Profiles by Task Groups for Heterogeneous Levels of Human Capital**



Source: authors.

Table 2. **Results of Fixed Effects Regression with Deflated Log Hourly Wages as Dependent Variable**

Log hourly wages	(1)	(2)	(3)	(4)	(5)
Education level					
VET	0.718*** (27.04)	0.497*** (18.20)	0.509*** (18.35)	0.488*** (14.54)	0.495*** (14.59)
Higher VET	0.696*** (19.98)	0.597*** (15.95)	0.581*** (15.69)	0.555*** (12.67)	0.567*** (12.89)
High School (Abitur)	-0.302*** (-9.50)	-0.280*** (-9.41)	-0.218*** (-7.13)	-0.231*** (-6.21)	-0.223*** (-5.93)
University	0.649*** (16.47)	0.613*** (12.95)	0.635*** (13.97)	0.602*** (11.34)	0.609*** (11.38)
Depreciation of education					
VET*pexper	-0.015*** (-17.40)	-0.010*** (-11.51)	-0.012*** (-14.35)	-0.011*** (-11.18)	-0.011*** (-11.13)
Higher VET*pexper	-0.016*** (-13.81)	-0.013*** (-10.25)	-0.014*** (-11.52)	-0.014*** (-9.70)	-0.014*** (-9.71)
High school*pexper	0.013*** (9.22)	0.011*** (8.01)	0.009*** (6.68)	0.009*** (5.43)	0.008*** (5.21)
University*pexper	-0.010*** (-9.43)	-0.010*** (-6.25)	-0.012*** (-8.78)	-0.012*** (-6.87)	-0.012*** (-6.82)
Experience					
pexper	0.040*** (7.71)	0.070*** (9.57)	0.070*** (10.38)	0.063*** (8.05)	0.064*** (8.10)
Depreciation of experience					
pexper-squared	-0.001*** (-41.64)	-0.001*** (-12.55)	-0.001*** (-13.70)	-0.001*** (-10.90)	-0.001*** (-10.68)
_cons	0.881*** (14.36)	-3.248*** (-24.00)	-2.347*** (-16.19)	-2.382*** (-14.07)	-2.347*** (-13.69)
Controls	No	+ personal	+ job	+ industry	+ tasks
Observations	262.7780	261.101	204.689	158.561	154.792
R-squared	0.407	0.425	0.388	0.386	0.385

Note: Dependent variable is Log hourly wages in constant prices.
* p<0.05, ** p<0.01, *** p<0.001, t statistics in parentheses, cluster robust standard errors.
Source: authors.

understanding of these processes' impact on human capital depreciation is critical for employees, employers, and policy makers alike.

This study analyzes skill obsolescence over the course of economic change, taking into account technological development factors such as the rate of new tools' application and the changing nature of work tasks. It was established that the human capital of workers performing predominantly non-routine interactive, non-routine manual, and routine cognitive tasks depreciates more rapidly than for other work task types. This can be explained by the two factors presented in Table 4. New digital solutions allow one to perform the above tasks more efficiently and are applied for these purposes more actively than elsewhere. The higher the technology application level, the more radically knowledge requirements change. As a result, the rate of basic human capital depreciation increases. Also, in a number of occupations, the use of digital technologies is changing particularly fast. First of all, this applies to jobs with a large share of non-routine manual tasks, where the accelerated digitalization leads to skill obsolescence. As this process continues, the work environment is likely to change even more dramatically, with the rate of skill obsolescence increasing even further.

Though in the case of routine tasks, human capital depreciates at a slower rate, this should not be seen as a positive factor since, as labor polarization studies show, workers performing routine cognitive tasks are gradually being replaced by technology. It is expected that in their present form, occupations based on such tasks will gradually disappear, which will accelerate skill depreciation even more.

Contrary to popular belief that technology is incapable of performing non-routine tasks, our results reveal a relatively high depreciation rate for workers in such occupations, despite the fact that demand for them is growing.

Common policy measures for dealing with these issues include improving workers' skills and increasing tertiary education enrollment. However, this does not protect against skill obsolescence either.

The main goal of tertiary education is creating general human capital applicable to a variety of non-routine work tasks. However, if knowledge related to an entire task group is expected to become obsolete due to external changes, even general higher

Table 3. **Results – Human Capital Depreciation by Task Groups**

Log hourly wages	Non-routine tasks			Routine tasks	
	analytical	interactive	manual	cognitive	manual
Education level					
VET	0.394** (-3.07)	0.677*** (-7.62)	0.541*** (-8.56)	0.635*** (-10.84)	0.503*** (-8.07)
Higher VET	0.462*** (-3.4)	0.803*** (-6.49)	0.572*** (-5.73)	0.792*** (-11.08)	0.563*** (-5.27)
High school (Abitur)	-0.244 (-1.83)	-0.181 (-1.69)	-0.15 (-1.87)	-0.08 (-1.36)	-0.316*** (-4.24)
University	0.393** (-2.68)	0.931*** (-6.01)	0.646*** (-4.04)	0.869*** (-10.14)	0.411* (-2.07)
Depreciation of education					
VET*pexper	-0.010** (-2.98)	-0.019*** (-4.54)	-0.015*** (-8.42)	-0.016*** (-9.48)	-0.012*** (-7.42)
Higher VET*pexper	-0.012*** (-3.30)	-0.023*** (-4.51)	-0.019*** (-6.27)	-0.021*** (-8.62)	-0.015*** (-5.27)
High school*pexper	0.008* (-1.97)	0.008 (-1.12)	0.000 (-0.01)	0.003 (-1.63)	0.011*** (-3.48)
University*pexper	-0.009* (-2.36)	-0.020*** (-3.97)	-0.016*** (-4.76)	-0.019*** (-6.36)	-0.011* (-2.46)
Experience					
pexper	0.031* (-2.43)	0.091*** (-3.58)	0.075*** (-3.94)	0.091*** (-7.44)	0.072*** (-3.34)
Depreciation of experience					
pexper-squared	-0.001*** (-3.85)	-0.001*** (-5.22)	-0.001*** (-6.05)	-0.001*** (-6.81)	-0.001*** (-5.66)
_cons	-1.798*** (-3.70)	-1.655*** (-3.52)	-3.561*** (-10.00)	-1.620*** (-6.68)	-3.077*** (-7.26)
Observations	46,523	17,716	30,927	62,462	28,791
R-squared	0.366	0.320	0.283	0.449	0.369

* p<0.05, ** p<0.01, *** p<0.001, t statistics in parentheses, cluster robust standard errors.
Source: authors.

education does not guarantee sustainability, which means that simply raising the level of education is no longer enough. The value of human capital based on university education is annually declining for all work task types, and doing so at a significant pace. Our findings suggest that for workers who predominantly perform non-routine manual tasks, the earnings-to-experience ratio may even worsen compared to other education levels less susceptible to depreciation. In the absence of lifelong learning, the initial investment in higher education may "dissolve". To prevent serious problems, it is necessary to expand the content of education and constantly invest in it, taking into account human capital depreciation.

Creating an inclusive labor market implies an opportunity for the most vulnerable population groups to acquire digital skills, which will require significant staff training efforts. For other groups, the ability to adapt and acquire new competencies to perform tasks which cannot be substituted by machines is crucial. It is advisable to pursue an integrated labor market and education policy aimed at countering human capital obsolescence. While

Table 4. **The Link between Job Tasks and Human Capital Obsolescence**

Task type	**Task example**	**Use of task-complementing technology**	**Change in job-related technology use**	**Human capital obsolescence**
Non-routine analytical	Researching, designing	medium	low	low
Non-routine interactive	Managing, entertaining	high	high	high
Non-routine manual	Repairing, serving	low	high	medium
Routine cognitive	Bookkeeping, calculating	high	medium	medium
Routine manual	Operating machines	low	low	low

Source: author's elaboration, based on (Muro et al., 2017) for data on technology use, task groups adopted from (Spitz-Oener, 2006) many countries have recognized the importance of this approach, further action is needed in the field of education. The findings of this study may help develop effective training programs to provide workers with opportunities to periodically upgrade their existing skills and acquire those in high demand. Educational policy should provide for "upgrading" competencies, allowing workers to quickly adapt to changing market conditions in a situation of increasingly rapid and radical technological progress. Companies interested in increasing workers' productivity need to expand training opportunities for them. As to workers, they need to be aware of the current developments and periodically plan for further training. If the efforts are focused on acquiring new skills and developing the existing ones, further technological development will yield significant benefits

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