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Human capital depreciation and job tasks

Sonja Walter, Jeong-Dong Lee
Technology Management, Economics and Policy Program, Seoul National University, Republic of Korea.

Abstract

This research aims to investigate the link between human capital depreciation and job tasks, with an emphasis on potential differences between education levels. We estimate an extended Mincer equation based on Neumann and Weiss's (1995) model using data from the German Socio-Economic Panel. The results show that human capital gained from higher education levels depreciates at a faster rate than other human capital. Moreover, the productivity-enhancing value of education diminishes faster in jobs with a high share of non-routine analytical, non-routine manual, and routine cognitive tasks. These jobs are characterized by more frequent changes in core-skill or technology-skill requirements.

The key implication of this research is that education should focus on equipping workers with more general skills in all education levels. With ongoing technological advances, work environments, and with it, skill demands will change, increasing the importance to provide educational and lifelong learning policies to counteract the depreciation of skills. The study contributes by incorporating a task perspective based on the classification used in works on job polarization. This allows a comparison with studies on job obsolescence due to labor-replacing technologies and enables combined education and labor market policies to address the challenges imposed by the Fourth Industrial Revolution.

Keywords: *Education; human capital; depreciation; skill obsolescence; tasks; technological change.*

1. Introduction

Education prepares workers to perform a certain set of tasks in the labor market, but the introduction of ICT and digital technology has changed how we work. Technologies substitute repetitive tasks and create new ones, leading to changes in skill requirements. Previously acquired skills through formal education and working experience lose their value in the labor market, causing the depreciation of economic skills, and thus, human capital.

As the speed of technological change increases amid the Fourth Industrial Revolution, the effect of economic skill obsolescence has become more severe. Skills obsolescence has previously been only a concern for individuals in technology-intensive sectors or occupations. However, with the ongoing digital transformation, most occupations have undergone changes in tasks due to the skill complementing or substituting effect of technologies. Consequently, the majority of jobs nowadays are subject to some form of skill obsolescence. This might be especially the case in jobs that are comprised of repetitive, routine intensive tasks. Due to new technologies, the skills of older workers become obsolete quickly, and the economic value of human capital decreases. To stay productive in the labor market, workers will need to upskill or even retrain to find new occupations.

Technological and organizational changes are expected to accelerate, and to affect all parts of the economy, increasing the risk of and the urgency to counteract skills obsolescence. Albeit these lingering effects, few studies consider factors of technological change when analyzing skill depreciation. To help close this gap, the study at hand attempts to examine the economic skill obsolescence by incorporating different task types into the analysis. Considering differences in the depreciation rate by job tasks contributes to the field in that it may provide fruitful insight into the depreciation patterns of human capital, enabling governments to design more effective education and lifelong learning policies. This is crucial in order to prepare workers for changing work environments.

The main body of this paper is structured into 4 sections. Section 2 presents the main literature and the theoretical framework. Section 3 proceeds with the data and methodology. Section 4 summarizes the findings, and finally, Section 5 concludes.

2. Background literature and theoretical framework

2.1. Types of skill obsolescence

Individuals acquire skills through education. Those skills depreciate over time and thus one's human capital depletes. There are two types of obsolescence (Arrazola & Hevia, 2004; De Grip & Van Loo, 2002; Neuman & Weiss, 1995), technical and economic obsolescence. Technical skills become obsolete due to the worker's physical aging or the un-use of skills. The obsolescence of economic skills is caused by the loss of market value of the worker's qualifications due to changes in the economic environment. We will focus on the latter in our analysis of human capital obsolescence.

2.2. Measurements of skill obsolescence

Skill obsolescence has not received much attention albeit its importance for human capital. Some scholars utilize Neuman and Weiss's (1995) operationalization of the depreciation rate which focuses on vintage effects. Depreciation is indirectly measured by the interaction between education and potential experience and indicates its effect on an individual's earning capacity following the Mincer model. It is based on the rationale that human capital depletes with the time since finishing formal education and potentially entering the labor force. This indirect measurement has the advantage that it captures the decreasing productivity effects through wages, which are the main worry for most countries (De Grip, 2006).

Murillo (2011) uses a modified version for the Spanish labor market and finds a schooling depreciation rate of 0.7% for 1995 and 0.4% for 2002, which increases with education level, and an experience depreciation rate of 3.8% and 1.8% respectively. Backes-Gellner and Janssen (2009) build upon an extended Mincer earnings equation and find that the rate of obsolescence is higher for workers in knowledge-based tasks compared to experience-based tasks. Lentini and Gimenez (2019) analyze sectoral differences of human capital depreciation in OECD countries for the period 1980 to 2005 and show that the depreciation ranges between 1% and 6% and is mainly significant in skill-intensive sectors regardless of the sector's technological intensity.

Other scholars model human capital and its depreciation mathematically and estimate the depreciation rate directly. Groot (1998) introduces a model and finds a depreciation rate of 11-17% for Britain and the Netherlands. Arrazola and Hevia (2004) obtain depreciation rates between 1.2% and 1.5% for Spain, depending on the type of sector and periods of unemployment. Also following this approach, Weber (2014) uses data for Swiss and shows that specific skills are prone to faster depreciation (0.9-1.0%) compared to general skills (0.6-0.7%). The spread in the depreciation rates is likely attributable to differences in measurement, as well as the variation in observation periods and datasets.

The aforementioned studies lay a good foundation for the analysis of human capital obsolescence, but most works do not incorporate the effects of technological developments which have transformed most advanced economies. Occupations become more complex and skill requirements change more quickly, highly depending on technology-related factors such as the type of job tasks, or the technology intensity of a sector. Thus, previously accumulated skills may become obsolete at a faster rate. As indicated by the results in Backes-Gellner and Janssen (2009), there are differences between knowledge and experience-based tasks, providing some evidence for the importance of incorporating a task perspective into the analysis. However, their specification does not consider the depreciation of formal education, making the results hardly comparable and unsuitable for evaluating the effectiveness of current educational systems. Other studies, for example, Weber (2014) or Lentini and Gimenez (2019) do only indirectly consider differences in the depreciation by occupational segment or sector. To close this gap, this study directly incorporates a task perspective based on the classification of job tasks adopted from the literature on job polarization while focusing on the depreciation of education. This enables a comparison with literature on skill obsolescence as well as works on job obsolescence.

2.3. Hypotheses

This subsection derives the hypotheses and elaborates on the role of tasks for the depreciation of human capital. Human capital is formed through education and experience. Thus, human capital depreciation comprises two separate effects, the depreciation of the educational stock, and the depreciation of the experience stock. Those two rates, combined with investments in human capital, determine its present value. Human capital obsolescence does not occur at the same speed for everyone. More advanced skills are expected to depreciate at a faster rate (Murillo, 2011; Neuman & Weiss, 1995) compared to basic skills which do not change much over time. Advanced skills acquired through university education contain state-of-the-art knowledge which might become less valuable as technologies evolve. Concurrently, general skills are thought to depreciate at a lower rate because they stay valid for longer periods and can be applied even in changing economic environments. Specific skills depend on the current state of technology when acquiring the education and will decrease in value when there have been external changes. Thus, we hypothesize:

H1a: *Workers with higher education levels have a higher depreciation rate than workers with lower education levels.*

H1b: *Workers with specific, vocational education (VET) have a higher depreciation rate than workers with general education*.

The next set of hypotheses addresses the link between the routineness of job tasks and skill obsolescence. Job tasks define which skills workers use throughout their careers. However, with ongoing technological progress, job tasks and skill demands might change more quickly, rendering old knowledge obsolete. This means that the present value of human capital depends not only on knowledge acquired through formal education, but also on the technological skills demanded by the job, and the skills to use those technologies and knowledge. Consequently, the depreciation rate of human capital may depend on how fast or often job-related knowledge or job-related technology change. Jobs that are exposed to changes in job-related technologies are characterized by a high share of non-routine analytical and routine cognitive tasks, i.e., programmers or bookkeepers, respectively. Those individuals are also susceptible to greater changes in job-related knowledge and skill requirements. In turn, workers in jobs that are not dependent on technology, i.e., those with a high share of interactive or manual tasks, are expected to have lower depreciation rates, thus:

H2a: *The depreciation rate is higher in jobs that are exposed to changes in job-related technologies compared to other jobs.*

H2b: *The depreciation rate is higher in jobs where the impact on job-related knowledge due to changes in technology is high compared to other jobs.*

3. Data and Methodology

To examine the depreciation rate and potential influencing factors, we utilize the German Socio-Economic Panel for the years 1984-2017 for the relationship between educational attainment and wages as well as other control variables for personal or job-related characteristics.

As presented in Section 2, the prevailing measurement of skill obsolescence is the indirect estimation of the depreciation rate. We model the depreciation rate of human capital depending on the decreasing effect of schooling on wages with time in the labor force using an extended earning function based on Neuman and Weiss (1995) and Mincer and Ofek (1982). The model accounts for the productivity-enhancing effect of education, the marginally decreasing effect of experience, and the depreciation of human capital related to the obsolescence of the worker's skills from formal education due to changes in the market environment. The education-specific depreciation is indirectly estimated in equation (1) as the interaction between the highest education level and potential years of experience *(*$Edu_i \times pexper_{it}$*)*. The coefficient of β_2 indicates how skill obsolescence affects the worker's earnings.

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

We use a panel fixed effects estimation with cluster robust standard errors to account for autocorrelation and heteroskedasticity of the error terms. Controls are included stepwise.

Next, we investigate whether the skill obsolescence depends on the main type of task a worker performs. To incorporate different occupational tasks, we construct a categorical variable from the German classification of occupations (KldB 1992) following the method suggested by Dengler, Matthes, and Paulus (2014). Based on the classification, each occupation is assigned one predominant task. These task groups are adopted from Spitz-Oener (2006) and Autor, Levy, and Murnane (2003) and differentiate between non-routine tasks (interactive, analytical, manual) and routine tasks (cognitive, manual).

We introduce the categorical variable *tasks* to differentiate between the different types of occupational tasks. This variable is first simply added to equation (1) to control for possible task-related wage effects. Finally, we estimate equation (1) groupwise for each of the 5 task groups to see how the depreciation rate varies for different types of job tasks.

Table 1. Results of fixed effects regression with deflated log hourly wages as dependent variable.

Log hourly wages	(1)	(2)	(3)	(4)	(5)
VET	0.718***	0.497***	0.509***	0.488***	0.495***
	(27.04)	(18.20)	(18.35)	(14.54)	(14.59)
Higher VET	0.696***	0.597***	0.581***	0.555***	0.567***
	(19.98)	(15.95)	(15.69)	(12.67)	(12.89)
University	0.649***	0.613***	0.635***	0.602***	0.609***
	(16.47)	(12.95)	(13.97)	(11.34)	(11.38)
VET*exper	-0.015***	-0.010***	-0.012***	-0.011***	-0.011***
	(-17.40)	(-11.51)	(-14.35)	(-11.18)	(-11.13)
Higher VET*exper	-0.016***	-0.013***	-0.014***	-0.014***	-0.014***
	(-13.81)	(-10.25)	(-11.52)	(-9.70)	(-9.71)
University*exper	-0.010***	-0.010***	-0.012***	-0.012***	-0.012***
	(-9.43)	(-6.25)	(-8.78)	(-6.87)	(-6.82)
exper	0.040***	0.070***	0.070***	0.063***	0.064***
	(7.71)	(9.57)	(10.38)	(8.05)	(8.10)
exper-squared	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(-41.64)	(-12.55)	(-13.70)	(-10.90)	(-10.68)
_cons	0.881***	-3.248***	-2.347***	-2.382***	-2.347***
	(14.36)	(-24.00)	(-16.19)	(-14.07)	(-13.69)
Controls	none	+ 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

4. Results

This section presents the results of the different specifications of our panel fixed effects regression, summarized in Table 1. In our preferred specification, column (4), the annual depreciation rate of education is the lowest (1.1%) for workers with VET degrees, followed by workers with a university degree (1.2%) and highest for workers with higher VET (1.4%). These values are in line with previous studies (Lentini & Gimenez, 2019; Neuman & Weiss, 1995; Weber, 2014) and add additional evidence to the higher depreciation rates for higher education levels. Moreover, these estimates indicate that skills from specific education deplete relatively faster. The depreciation rate for one additional year of potential experience is relatively low (0.01%) compared to other studies (Murillo, 2011).

Next, we present the results of our regression by predominating task-type which are graphically summarized in Figure 1. We show that the depreciation rate varies by education level and job tasks. Especially in non-routine analytical tasks, non-routine manual tasks, and routine cognitive tasks, skills are at higher risk of depreciating. Those job tasks are exposed to more frequent changes in job-related technology and likely to be affected more by it.

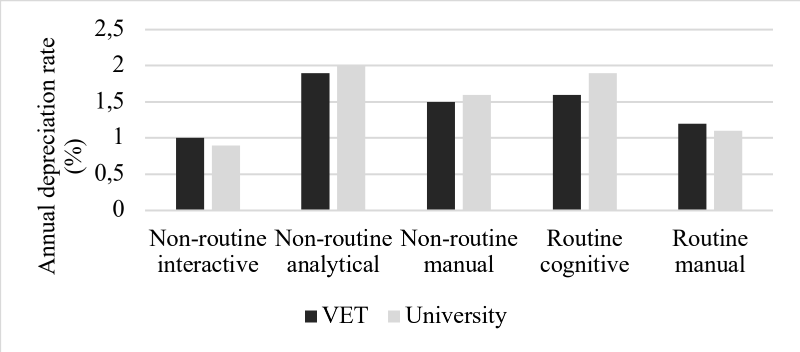

Figure 1. Results for the depreciation rate by predominant type of job tasks.

Table 2. The link between job tasks and skill obsolescence.

Task type	Example	Change in job-related technology	Impact on job-related knowledge	Skill obsolescence
Non-routine interactive	Lobbying, entertaining	low	low	low
Non-routine analytical	Programming, designing	high	high	high
Non-routine manual	Repairing, renovating	medium	medium	medium
Routine cognitive	Bookkeeping, calculating	high	low	medium
Routine manual	Operating machines	medium	low	low

5. Conclusion

New technologies change working environments and skill demands, rendering skills acquired through formal education obsolete. The present study analyzed the economic obsolescence of skills due to changes in the economic environment and incorporated factors related to technological change, i.e., technology intensity and occupational tasks. The results bring forth that skills in non-routine analytical, non-routine manual and routine cognitive tasks depreciate faster than skills in other tasks. This may be attributable to frequent updates in job-related technology and its impact on job-related knowledge, as summarized in Table 2. Additionally, routine cognitive tasks are in the process of being substituted by technologies, increasing skill obsolescence. The results show that tertiary education does not protect workers against skill obsolescence. This finding is important because it suggests that increasing the education level of the workforce is not enough.

With the ongoing digital transformation, more dramatic changes in work environments are likely, possibly increasing the rate of skill obsolescence further. While the results of the current study indicate that human capital depreciation will be smaller in routine tasks, this should not be interpreted as good news; routine-intensive occupations are likely to gradually disappear in their current form. In turn, the depreciation rate for non-routine tasks is relatively high, while the demand for those job tasks increases. Thus, changes in educational content and investments are inevitable to avert serious problems.

These developments put pressure on governments to provide effective education policies targeting the obsolescence of human capital. While many countries have realized the importance, more education measures are needed to prepare the workforce for the ongoing changes. This study may help policymakers to design effective training programs that allow professions to update their qualifications periodically to incorporate the most recently demanded skills. Most importantly, educational policies need to incorporate technological knowledge demanded by the workplace and enable workers to adapt their abilities to changing market conditions quickly amid more rapid and disruptive technological advances.

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