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Skill Obsolescence, Vintage Effects and Changing Tasks*

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Abstract

Human capital is no doubt one of the most important factors for future economic growth and well-being. However, human capital is also prone to becoming obsolete over time. Skills that have been acquired at one point in time may perfectly match the skill requirements at that time but may become obsolete as time goes by. Thus, in the following paper, we study the depreciation processes of the human capital of workers performing different types of tasks with different skill requirements over a period of more than twenty years. We argue that two types of tasks must be distinguished: *knowledge-based tasks* and *experience-based tasks. Knowledge-based tasks* demand skills depending on the actual stock of technological knowledge in a society whereas *experience-based tasks* demand skills depending on personal factors and individual experience values. We show, by applying Mincer regressions on four different cross sections, that the human capital of people performing *knowledge-based tasks* suffers more from depreciation than the human capital of individuals performing *experience-based tasks.*

Keywords: Human Capital, Skills, Mincer regressions

JEL Classification: J0,J2, J3

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1. Introduction

Human capital is no doubt one of the most important factors for future economic growth and well-being. However, human capital is also prone to becoming obsolete over time. Skills that have been acquired at one point in time may perfectly match the skill requirements at that time but may become obsolete as time goes by. The more innovative an economy is, the more likely it is that particular technological or methodological skills will become obsolete.

Spitz-Oener (2006) showed that the composition of tasks demanded by different occupations has changed considerably over the last decades. As an extension of her study we investigate in this paper whether the human capital depreciates differently for workers performing different types of tasks with different skill requirements over a period of more than twenty years. Therefore, we argue that two types of tasks must be distinguished: *knowledge-based tasks* and *experience-based tasks.* We define *knowledge-based tasks* as tasks depending strongly on the general stock of technological knowledge available to society, whereas *experienced-based tasks* are defined as tasks demanding personal characteristics that can be improved by gaining more and more experience. We further argue that the human capital of people performing *knowledge-based tasks* strongly suffers from depreciation, whereas the human capital of individuals performing *experience-based tasks* does not. This is mainly because the general stock of technological knowledge available to a society at a given point in time is changing and rising. Therefore, technologies and work processes are changing. If certain human capital is strongly related to older technologies or work processes, it becomes worthless with the disappearance of the technologies and processes. As *knowledge-based tasks* by definition depend on the actual stock of technological knowledge we argue that individuals performing mainly *knowledge-based tasks* in their jobs should suffer more from skill obsolescence than individuals performing mainly *experience-based tasks* which are timeless and comparatively independent from actual technologies.

We investigate this relationship by observing different influences of task combinations on individual incomes. In order to study such effects, we need a database with detailed information on tasks that people perform at the workplace over a long time span. Therefore, we use the four waves of the so-called BIBB / IAB Qualification and Career Survey because it not only deeply specifies the tasks individuals perform in their jobs, but also covers a time span of more than twenty years, which is a prerequisite to studying the above-mentioned vintage effects.

Making use of extended Mincer type earnings regressions (similar to an approach developed by Neuman and Weiss 1995), we find the following: workers performing different types of tasks are affected differently by skill obsolescence. In more detail workers face greater skill obsolescence whenever the share of *knowledge-based tasks* is high in comparison to the share of *experience-based tasks.* These results provide novel insights in the way of looking on experience earnings profiles and extend the literature on skill obsolescence since previous literature distinguished only between differences in the obsoleteness of various groups of workers (for example, with different educational backgrounds), but not between differences in obsoleteness depending on the types of tasks a person performs.

The rest of the paper is organized as follows. In section 2, we present previous literature and our own theoretical considerations in more detail. In section 3, we present our estimation strategy. In section 4, we describe the data. Section 5 follows with the results, and section 6 concludes the article.

2. Literature and theory

Rosen (1975) and Ben-Porath (1967) were among the first to study depreciation or obsolescence due to technological progress. They point out that human capital loses value because it is related to technologies that are no longer used. Workers of recent vintages are beneficiaries of new technologies as they grew up with recent knowledge about the technology and were adapted to it during school, further education or training. Thus, younger workers can be more productive than workers of older vintages if the older workers do not continue investing in recent human capital. As soon as older technologies are no longer used, skills connected to them become obsolete. As Rosen (1975) argues more comprehensively, some (technological) knowledge may turn out to be incorrect or less general than it was supposed to be in former times.

The empirical literature investigates skill obsolescence or depreciation using different approaches (for an overview, see De Grip et al. 2002). Some studies focus on subjective measures or certain labor market outcomes, such as unemployment or the transition from education to work. Ludwig and Pfeiffer (2005), for example, show, by using a subjective measure, that human capital accumulated during vocational training is confronted with a steadily rising rate of depreciation. However, apart from that, most studies focus on wages. While some try to measure the rate of depreciation exactly, such as Arrazola and de Hevia (2004) or Groot (1998), others focus more on the detection of vintage effects or depreciation in general (Neuman & Weis 1995, Weiss & Lillard 1978).

Thus, the literature supports the theory that workers who entered the labor market in earlier years and have acquired older skill vintages can be expected to have less up-to-date knowledge than workers entering more recently and holding more recent skill vintages.[1] This is driven mainly by the fact that older workers invest less time in accumulating human capital and therefore, accumulate less of the steadily growing stock of recent technological knowledge.[2]

[1] Of course, new knowledge or new technologies do not always completely replace older knowledge. New developments can also complement existing skills. Weinberg (2004), for example, shows that newer technologies complement the skills of older workers, but only to a certain degree. Nevertheless, he finds that younger workers are better able to adapt to new technologies.

However, we argue that obsolescence due to external changes, such as technological progress will not affect every skill set equally. The rate of skill obsolescence rather depends on the tasks a worker must perform or the objectives he is confronted with in his working life. We argue that two types of tasks must be distinguished, which we will call *knowledge-based tasks* and *experience-based tasks* throughout the rest of the paper.

We argue that *knowledge-based tasks* depend strongly on the actual stock of technological knowledge in a society and therefore, we expect people performing mainly these kinds of tasks to strongly suffer from depreciation and skill obsolescence. Writing computer programs, for example, depends strongly on technological developments in this field. Currently, for instance, many business applications are written in .NET or Java. Younger workers who are trained in these programs have productivity advantages in comparison to older workers who grew up with Fortran or Pascal.

In contrast, we define *experience-based tasks* as tasks depending on personal factors and abilities that grow with individual experience. Selling or negotiating are two examples for these kinds of tasks. These tasks demand a good sense for human behavior or certain personal characteristics such as sympathy or self esteem and depend less on technological knowledge. Thus, we expect them to suffer less from depreciation due to technological change. Instead, it seems reasonable to assume that more experienced workers (older vintages) have even an advantage in performing these kinds of tasks.

So far we only considered the depreciation due to external factors such as the technological development. But skills could also become obsolete due to internal factors; i.e. simply due to the aging of individuals and this aging affecting their individual productivities. This kind of skill depreciation is called internal depreciation[3] and the psychological and medical literature can provide additional helpful insights on this. It distinguishes between different kinds of intelligence. On the one hand, the concept of fluid intelligence refers to abilities such as the fast processing of information or the ability to understand abstract concepts. On the other hand, the concept of crystalline intelligence refers to skills based on experience and social competence, as well as the ability of ambivalence. They argue that fluid intelligence depreciates due to biological aging from thirty years onwards. Crystalline intelligence, however, does not suffer from depreciation due to aging (Sternberg et al. 2005, Baltes et al. 2005, Compton et al. 2003, Skirbekk et al. 2005).

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2 Mincer (1974) states three reasons for this: First, in finite lifetimes, people have a shorter period to gain the returns of investments. Second, each investment reduces the present value of net gains. Third, forgone earnings due to investments increase with tenure as a result of the previous investments in on the job training, make working time more valuable. In fact, many empirical studies support this view as older workers invest significantly less in on the job training (see for an overview Groot, 1998).

3 Neuman and Weiss (1995) distinguish between internal and external depreciation. Thereby, internal depreciation refers to the loss of skill due to aging or physical diseases.

One can argue that the handling of technologies or technology related knowledge requires abilities such as processing information or understanding abstract concepts. Hence, fluid intelligence is probably more important to perform *knowledge-based tasks* properly than *experience based tasks.* In contrast one can argue that *experience-based tasks* demand abilities such as social competence and therefore particularly benefit from crystalline intelligence. Thus, the evidence from psychological literature on aging supports our view that skill obsolescence is larger for workers performing mainly *knowledge-based tasks* than for workers performing mainly *experience-based tasks.* Moreover, as crystalline intelligence is important to perform *experience-based tasks* one can conclude that older workers should even benefit from focusing on these kinds of tasks.

In sum, we can conclude that the skills needed to perform *knowledge-based tasks* should suffer more from skill obsolescence then the skills needed to perform *experience-based tasks.* In fact, one could expect that the latter improve with experience. In the following, we try to measure this effect indirectly by applying an idea from Neuman and Weiss (1995) to experience earnings profiles in cross sectional data.

3. Estimation strategy

In this section, we show what we can learn about human capital depreciation from estimated experience earnings profiles. Therefore, we follow Neuman and Weiss (1995) and Ramirez (2002) by applying an idea from Mincer (1974) to cross sectional data. The main focus of our investigation will be the year of experience at which earnings profiles peak. In detail, we look for the earnings peaks for different groups of workers performing different kinds of tasks.

To clarify our approach we give a short overview of the classical Mincer model with depreciation. Mincer (1974) stated that an individual's earnings capacity E_j after j years in the labor force will be approximately

$$\ln E_j = E_0 + \sum_{t=0}^{j-1} r_t k_t \,. \qquad (1) \qquad \text{(Mincer, Eq. 1.14)}$$

E_0 is the earnings capacity when the individual starts working, and r_t is the rate of return in on-the-job training; $k_t = \dfrac{C_t}{E_t}$ is the ratio of investment in on-the-job training (C_t) to gross earnings (E_t), and it is assumed that $k_t \leq 1$ and decreases over time. Equation (1) represents the so-called standard Mincer model. However, Mincer (1974) himself expanded this model by incorporating a rate of depreciation δ_t. Thus, equation (2) follows:

$$\ln E_j = E_0 + \sum_{t=0}^{j-1} (r_t k_t^* - \delta_t) \,. \qquad (2) \qquad \text{(Mincer, Eq. 1.21)}$$

Whereby $> k_t^*$ is now the ratio of gross investment with C_t^* . In empirical data we are able to observe net earnings rather than the earnings capacity. If Y_j are the net earnings at time $t = j$, one can show that:

$$\ln Y_j = \ln Y_{j-1} + \ln(1 + r_{j-1}k_{j-1}^* - \delta_{j-1}) + \ln(1 - k_j^*) - \ln(1 - k_{j-1}^*) \,. \tag{3}$$

(Mincer, Eq. 1.23)

Thus, earnings will peak when the right hand side of equation (3) equals the left hand side. Hence, earnings peak if we have:

$$\delta_{j-1} = (1 + r_{j-1})k_{j-1}^* - k_j^* \,. \tag{4}$$

As k_j^* is assumed to be strictly linear and decreasing, equation (4) indicates that earnings will peak earlier if the rate of depreciation is higher. The distance between $k_{j-1}^* - k_j^*$ is bigger at earlier stages of a worker's career. Like Neuman and Weiss (1995) and Ramirez (2002), we argue that the rate of depreciation is not equal for everyone. In contrast to Neuman and Weiss (1995), we are not interested in understanding how skill obsolescence works for the human capital of different education groups. Instead, as previously mentioned, we argue that skill obsolescence depends on the tasks a worker performs. Hence, we have $\delta(kbt, ebt)$ where kbt denotes the amount of *knowledge-based tasks* and ebt denotes the amount of *experience-based tasks* in an individual's job.

Thus, from our theory we expect the rate of depreciation to be higher for people performing jobs demanding a higher amount of *knowledge-based tasks* given the amount of *experience-based tasks.* Thus, $\left.\frac{\partial \delta}{\partial kbt}\right|_{ebt} > 0$. Therefore, given the amount of *experience based tasks,* the earnings functions should peak earlier the higher the amount of *knowledge-based tasks.* As we expect the reverse to be true for *experience-based tasks,* we have $\left.\frac{\partial \delta}{\partial ebt}\right|_{kbt} < 0$.

To prove our hypotheses, we apply the following extended Mincer type earnings function:

$$\begin{aligned}\ln y_i = \beta_0 + \beta_1 \exp_i + \beta_2 \exp_i^2 + \beta_3 kbt_{ij} + \beta_4 kbt_{ij} * \exp_i + \beta_5 ebt_{ij} \\ + \beta_6 ebt_{ij} * \exp_i + X_i\beta_7 + \varepsilon_i \,.\end{aligned} \tag{5}$$

$\ln y_i$ stands for the logarithm of the observed net earnings of individual i; $\exp_i$ and its squared term are the years of labor market experience; β_1 and β_2 are the respective coefficients. X_i is a matrix containing further controls, such as schooling, professional status, gender and firm size. β_7 is the respective coefficient vector. ε_i is assumed to be a normal distributed error term with mean zero. As we are interested in measuring the effects of certain task compositions on experience earnings profiles, we extended the classical Mincer model by kbt_{ij}, a variable measuring the average share of all *knowledge-based tasks* observable in the data for individual i's job j, and by ebt_{ij}, the average share of all *experience-based tasks* observable in the data for individual i's job j. Moreover, we interacted the variables kbt_{ij} and ebt_{ij} with the experience variable $\exp_i$. β_3 to β_6 are the respective coefficients[4]. Thus, as we expect the earnings profile to peak earlier for an increasing amount of *knowledge-based tasks* (given the amount of *experience-based tasks*) the coefficient β_4 should be negative. In the same way, the coefficient β_6 should be positive as we expect the earnings profiles to peak later if the amount of *experienced-based tasks* is large.

In the language of Mincer (1974), equation (6) gives the experience value at which earnings peak (i.e., the derivate of (5) with respect to $\exp_i$ solved for $\exp_i$). The left hand side of (6) will decrease as *kbt* rises if β_4 is negative and increase if *ebt* rises and β_6 is positive (note that in Mincer regressions β_1 is expected to be positive and β_2 is expected to be negative).

$$\exp = f(\beta_1, \beta_2, \beta_4, \beta_6) = \frac{-(\beta_1 + \beta_4 kbt + \beta_6 ebt)}{2\beta_2}\,. \tag{6}$$

However, one could also give two more intuitive interpretations for the expected regression results.

First, if β_4 in (5) is negative, it indicates that the marginal rate of return for experience decreases faster if the share of *knowledge-based tasks* is higher, whereas a positive β_6 indicates that the marginal rate of return for experience decreases slower if the share of *experience-based tasks* is higher. Thus, under the assumption of equal investments in human capital, the value of one year of human capital investments decreases faster for people performing a high share of *knowledge-based tasks* then for people performing a comparative high share of *experienced-based tasks.* This indicates a higher rate of depreciation for people performing mainly *knowledge-based tasks* in their jobs.

Second, one could give an alternative interpretation of the maximum of experience earnings profiles in cross sections. As we observe individuals with different amounts of work experience at one point in time, an early peak indicates that many individuals with relatively short working careers earn more than individuals with longer careers. Thus, one could argue, as individuals with shorter careers usually have more recent human capital then individuals with longer careers, that there is a taste for fresh human capital in the labor market. In other words, individuals with longer careers and a high amount of human capital suffer due to skill obsolescence and earn less than their younger colleagues. This interpretation is more in line with a recent model by Laing, Palivos and Wang (2003).

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4 We can interpret the coefficients β_4 and β_6 similar to the coefficient hexpsch of equation (7) in Neuman and Weis (1995).

4. Data

For our empirical investigation, we used data from the Qualification and Career Survey. This survey is carried out by the German Federal Institute for Vocational Training (Bundesinstitut für Berufsbildung) and the research Institute of the Federal Employment Service (Institut für Arbeitsmarkt- und Berufsforschung). It sampled a representative group of the German workforce in 1979, 1985 / 86, 1991 / 92 and 1998 / 99. Each sample contains around 30,000 observations.

We only cover people between the ages of 18 and 65 having no more than 45 years of experience. We excluded individuals from East Germany (because they are not observable in every wave), foreigners, the unemployed, self-employed workers and individuals working less than 35 hours per week. In addition, we excluded workers with implausible high or low wages by dropping one percent of people with the highest and one percent of people with the lowest wages. These constraints result in 15,278 observations in 1979, 15,330 observations in 1985 / 86, 13,808 observations in 1991 / 92, and 11,871 observations in 1998 / 99.

The underlying data set refers to tasks that people have to perform to properly do their jobs. Hence, people had to choose these tasks from a given list. As mentioned in the second section, we distinguished between two types of tasks. The first category refers to *knowledge-based tasks* and the second to *experience-based tasks.* These categories were constructed as presented in Appendix table A2 for each wave.

Thus, *knowledge-based tasks* are all tasks for which it can be assumed that they depend strongly on a given type of technical knowledge at a certain point in time. As an example one can take *"repairing machines, equipment, etc.".* It is obvious that a person has to have knowledge of the machine's technology. If this technology changes, the worker's abilities will no longer fit with the skill requirements to repair these machines. Thus whenever technology is involved that is not timeless, we expect to find strong skill obsolescence effects. However, this category does not only include technology in the sense of machinery, or hard- and software, but also for example legal or institutional regulations which also might strongly change over time. An example that one could think of are changing collective agreements, labor law or environmental law: the rules that have to be met at one point in time may be different from the rules that have to be met at another point in time. Thus, the particular knowledge from one time period may be completely obsolete in a later period. Moreover, these tasks demand analytical skills and therefore fluid intelligence which we also relate to *knowledge-based tasks.* A complete overview of *knowledge-based tasks* in comparison to *experience-based tasks* is given in table A2 in the appendix. We expect all tasks on the right side of the tables in A2 to be affected quite strongly over time by external changes in the stock of technological knowledge. In contrast, we argue that all tasks on the left side of the tables in A2 are not affected by external changes in the stock of technological knowledge. Instead, the tasks on the left side depend more on personal factors which may even increase over time due to increased experiences. Thus, we do not expect strong depreciation effects for these types of tasks.

Compared to Spitz-Oener (2006) who also suggested a separation of different tasks based on the same variables of the BIBB / IAB data set, our categories are different in two ways. First, we use a more complete set of tasks in the single waves then she did. Since we were not interested in observing changes in task combinations from wave to wave, we were not faced with the same restrictions like Spitz-Oener (2006). Because our analysis uses each of the single waves separately we were not forced to use only comparable tasks in each of the waves. Thus, we decided to incorporate more tasks in our categories even if they were not observable in every wave. Second, our definition criterion reference is quite different because we were interested in the distinction between task depending on technological knowledge and tasks depending on personal factors and communication skills. For example, in her paper tasks such as equipping machines are considered to be *routine manual tasks.* In our paper we argue they are *knowledge-based tasks* because workers performing these tasks have to deal with potentially changing technologies. The question whether a task at a given point in time is routine or non-routine is not important to us; for our analysis it is only important whether for a given task at a given time the job requirements are expected to be the same as for a task at a future point in time.[5]

In addition, to consider the fact that task sets differ quite widely between the single cross sections, we will calculate two versions of the measure to check the robustness of our results.

First, we created a measure in a similar fashion to Spitz-Oener (2006) (with different categorization). Thus, we divided the number of activities that an individual performs in each category (*knowledge based tasks / experience based tasks*) by the total number of observable tasks in that category. Afterwards, we calculated the average of this task measure for each of the 83 job categories listed in Appendix table A3. This was done for every wave separately as task sets observable in each wave differ strongly. Thus, every job has four different task measures for both categories (one for each wave).

A second measure was created by pooling the sample of all four waves and calculating an overall average of the first measure for each occupation and task category, which is constant over all waves. Hence, there is just one pooled value that differs for each job and category but is the same in each wave.

5 Note that we assign the average share of all observable *knowledge-based* and the average share of all observable *experienced-based tasks* to every job listed in Appendix A3. Hence, if for one job the average share of all observable *knowledge based tasks* over all observed persons in that job is high, it indicates that *knowledge-based tasks* are important to that job; i.e., on average, many individuals in that job perform *knowledge-based tasks.* We believe this measure to be far more reliable than creating a similar measure on the individual level where we do not really know how important the respective tasks are to the individuals.

To give an example of the first measure, we observe that mechanics performed on average around 6 percent of *knowledge based tasks* and 2 percent of *experience based tasks* in 1979. For 1985 / 86 we have 24 percent and 6 percent, for 1991 / 92 we have 25 and 6 and for 1998 / 99 we have 52 and 37 percent. Note that the values differ quite widely and are not comparable over time as the questionnaires were different in every wave. However, for the second measure, mechanics perform on average 24 percent of all observable *knowledge based tasks* and around 9 percent of all observable *experience based tasks.*

The first approach has the advantage that we can test whether our expectations hold independent of the fact that the tasks we are able to observe in every wave differ quite strongly. Nevertheless, it has the drawback that we may measure different effects in every wave. The second approach ensures that we measure a similar effect in every wave by considering the average of all observable tasks weighted by the individuals performing the respective jobs in every wave. The drawback of the second approach is that we have to assume that the average task combinations did not change within jobs over time. The measures will be used as indicators for kbt_{ij} and ebt_{ij} of equations (5) and (6).

For y_i we use monthly wages. The experience measure $\exp_i$ was directly obtained from the survey. Moreover, we added certain controls in X_i. We used a set of dummies corresponding to the degrees in the German education system as variables for the level of general education. Thus, we created a dummy taking the value of one whenever an individual holds neither an apprenticeship degree nor a university degree (low education). A second dummy is one if the individual holds an apprenticeship degree (medium education), and a third is one for university graduates (high education). Moreover, we used a dummy for gender, taking the value of 1 if the person is female and 0 otherwise. Further controls were added for the professional status of the worker, including dummies for unskilled, blue collar workers (skilled), foremen, white collar workers and civil servants. Firm size dummies were also included in the regressions. Descriptive statistics on all explanatory variables can be found in Appendix table A1.

5. Results

Descriptive statistics:

In table 1, we present some detailed descriptive statistics of our task measures for the pooled sample. In the descriptive statistics, we will only refer to the pooled sample as the statistics give qualitatively the same results if we look on each wave separately.

In the first and second column we examine how the tasks are distributed across different levels of professional status. Thus, the first row in the third column tells us, for example, that unskilled workers perform around 10 percent of all observable *knowledge-based tasks* and only around 4 percent of all *experience-based tasks.* In every other professional category we have higher average values. For blue collar workers, we observe a strong focus on *knowledge-based tasks,* i.e., around 19 percent of *knowledge-based tasks* and only 7 percent of *experience-based tasks*. In contrast the difference between *knowledge* and *experience-based tasks* is rather small for white collar workers. This makes sense if one considers that blue collar workers probably participate directly in the production process and have less contact with clients. White collar workers, in contrast, can either perform technical jobs, like engineers or computer technicians, or highly client-related jobs in the service sector. The same reason could explain why civil servants perform a rather large share of *experience-based tasks* as these jobs are mostly less related to technology.

Table 1

Descriptive statistics of task measures

Professional status			**Education**			**Gender**		
	kbt	*ebt*		*kbt*	*ebt*		*kbt*	*ebt*
unskilled	10.260	3.866	low education	9.313	6.624	female	10.963	18.984
blue collar	18.923	7.022	medium education	16.938	16.916	male	19.099	16.048
white collar	23.427	19.940	high education	25.632	33.993			
civil servant	16.598	25.592						

In the fifth and sixth columns we show the tasks distributions according to educational level. The results tell us that a larger amount of human capital in the form of educational level leads people to perform a larger set of different tasks. This holds for either *knowledge* or *experience-based tasks* as the shares are (at around 25 and 34 percent) highest for individuals with a university degree. Individuals holding neither an apprenticeship degree nor a university degree, in contrast, have the lowest values for both task categories.

The last two columns of table 1 present the results of the task distribution according to worker gender. The first row tells us that females perform a bigger share of *experience-based tasks,* whereas the second row shows that males perform on average more *knowledge-based tasks*. This result is in line with the fact that in Germany, more men study technical subjects or hold jobs involving technical content.

Regression results for the first specification:

To show how the composition of tasks affects workers' wages, we present the estimation of equation (5) according to our first measure in table 2. Hence, in table 2 we stayed with the task measure, which differs in every wave. We estimated eight specifications; two for each wave.

Thus, we have one specification where we regressed the logarithmic monthly wage on our main variables of interest without further controls (i.e., equation (5) without $X_i\beta_7$) and one specification with the full set of variables.

Table 2

Mincer type regression with logarithmic monthly wage as dependent variable (first specification)

	1979		1985/86		1991/92		1998/99	
	I	II	III	IV	V	VI	VII	VIII
experience	0.030***	0.021***	0.032***	0.025***	0.029***	0.021***	0.023***	0.019***
	[28.00]	[21.82]	[30.13]	[25.10]	[24.38]	[19.42]	[14.66]	[12.87]
(experience squared)*100	–0.059***	–0.043***	–0.062***	–0.052***	–0.049***	–0.038***	–0.031***	–0.029***
	[29.04]	[24.00]	[29.67]	[27.53]	[22.62]	[19.94]	[13.13]	[13.87]
kbt	0.042***	0.015***	0.018***	0.006***	0.018***	0.007***	0.010***	0.004***
	[21.73]	[8.66]	[27.04]	[9.53]	[26.42]	[10.72]	[20.60]	[9.56]
*kbt*exp**100	0.013	–0.002	–0.001***	0.004	–0.018***	–0.005**	–0.009**	–0.004**
	[1.25]	[0.21]	[2.94]	[1.27]	[6.05]	[2.19]	[4.42]	[2.53]
ebt	0.007***	–0.004**	0.011***	0.002***	0.012***	0.004***	0.005***	0.001***
	[2.26]	[3.78]	[18.58]	[4.03]	[18.31]	[6.37]	[13.56]	[3.37]
*ebt*exp**100	0.025**	0.053***	0.016***	0.02***	0.008***	0.013***	0.001	0.005***
	[2.52]	[6.42]	[5.49]	[7.64]	[2.96]	[5.17]	[0.54]	[3.51]
Controls	no	yes	no	yes	no	yes	no	yes
Observations	15278	15278	15330	15330	13808	13808	11871	11871
R-squared	0.2	0.4	0.26	0.45	0.23	0.44	0.18	0.37

Robust t statistics in brackets * significant at 10%; ** significant at 5%; *** significant at 1%. Controls are sex, firm size, type of education and professional status.

The coefficients of experience and experience squared show the typical signs and power. However, let us take a look at the main variables of interest. If we first consider the variables on the share of all possible *knowledge-based tasks* (*kbt*) and the share of all possible *experience-based tasks* (*ebt*), we find significant positive values throughout all specifications apart from specification II, where the variable of *ebt* is significant and negative. However, apart from specification II, the results indicate that whenever the share of tasks demanded by a certain job rises, the person earns a significantly higher wage and it is irrelevant whether the tasks are *knowledge-based* or *experience-based.* This outcome is reasonable from a human capital perspective. A higher demand of various tasks in a job should lead to a higher ability and therefore higher individual productivity.

More interestingly, the share of all possible *knowledge-based tasks* always gives us a bigger coefficient then the share of *experience-based tasks.* Thus, at the beginning of a career (with 0 years of experience), a one percent increase in the share of *knowledge-based tasks* always leads to a higher wage advantage than a one percent increase in the share of *experience-based tasks.*

Now, considering the interaction term *kbt*exp* for *knowledge-based tasks,* we have either significant negative coefficients for specifications III and V to VIII or coefficients that do not differ from zero. This indicates that a given share of *knowledge-based tasks* will either not give individuals an extra wage advantage if they progress in their careers or can even harm them with respect to workers holding jobs with a lower share of *knowledge-based tasks.* With respect to the theory of Mincer (1974), specifications III and V to VIII confirm our theory that the rate of human capital depreciation is higher when the share of *knowledge-based tasks* is higher. The coefficients are significant and negative and therefore indicate an earlier peak holding everything else constant. Thus, the marginal rate of return for experience decreases at a faster rate if the share of *knowledge-based tasks* is high in a job. However, in specifications I, II and IV, our theory is not confirmed by significant negative values.

Let us take a look at the interaction terms for *kbt*exp* for *experience based tasks.* All columns show significant positive effects. Hence, even if the wage advantage is somewhat higher for workers performing jobs with a high demand of *knowledge-based tasks* at the beginning of the career, performing jobs with a high demand of *experience-based tasks* seems to benefit mainly workers with longer careers. Thus, the earnings profiles peak later if the share of *experience-based tasks* is higher in a given job, assuming everything else to be constant. The marginal rate of return decreases slower for individuals performing higher shares of *experience-based tasks* in their jobs.

Regression results for the second specification:

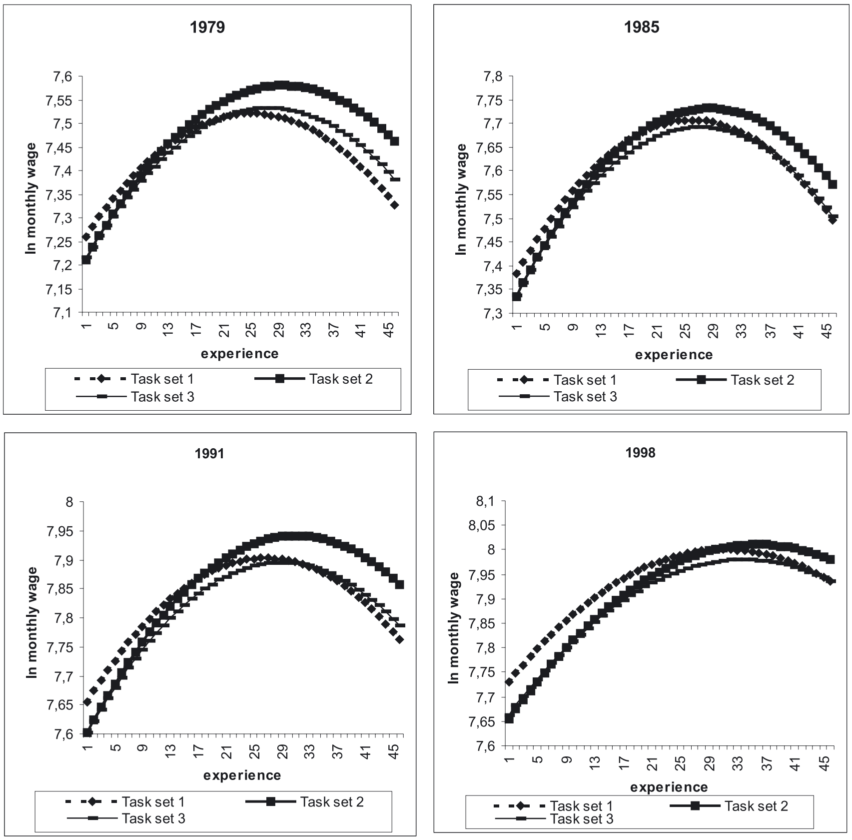
In table 3 we present the results for our second specification measure of tasks. Here we present *X* specifications as we added two specifications of the pooled sample; one with controls and one without controls. Now, as explained above, we have the same measures for the task portfolios in every wave, and hence, results are more comparable. As in table 2, the results in table 3 support our theory. We also observe that the coefficients of *kbt* and *ebt* are positive and significant and the coefficient of *kbt* is always higher. Moreover, we observe a significant negative coefficient for *kbt*exp* and a positive one for *ebt*exp.* Thus, as predicted by our theory, experience earnings profiles peak earlier if the share of *knowledge-based tasks* demanded by a job is higher given the share of *experience-based tasks* and vice versa. Moreover, the magnitudes of the coefficients seem to be quite stable and cannot be controlled away by the incorporation of further control variables. This indicates that we indeed measure a similar effect in every wave.

To illustrate the results of table 3 we plot the earnings profiles according to the estimation results in table 2 for three hypothetical task sets. The first task set puts a high weight on *knowledge-based tasks* and a low weight on *experience-based tasks.* The second task set puts a high weight on *experience-based tasks* and a low weight on *knowledge based tasks* and the third task set puts equal weights on both *knowledge* and *experience-based tasks.*

Table 3: **Mincer type regression with logarithmic monthly wage as dependent variable (second specification)**

	1979		1985 / 86		1991 / 92		1998 / 99		Pooled	
	I	II	III	IV	V	VI	VII	VIII	IX	X
experience	0.034***	0.024***	0.032***	0.025***	0.027***	0.021***	0.023***	0.020***	0.029***	0.022***
	[28.81]	[23.04]	[31.84]	[26.82]	[23.78]	[19.95]	[17.24]	[16.21]	[53.42]	[43.92]
(experience squared)*100	–0.06***	–0.045***	–0.062***	–0.052***	–0.047***	–0.038***	–0.031***	–0.03***	–0.051***	–0.041***
	[29.18]	[24.68]	[29.68]	[27.71]	[21.81]	[19.68]	[13.38]	[14.17]	[48.60]	[43.48]
kbt	0.017***	0.006***	0.017***	0.006***	0.019***	0.008***	0.018***	0.009***	0.018***	0.007***
	[25.45]	[9.77]	[26.50]	[9.88]	[27.83]	[12.63]	[23.73]	[12.19]	[52.02]	[22.41]
*kbt***exp**100	–0.019***	–0.015***	–0.013***	–0.001	–0.019***	–0.01***	–0.018***	–0.011***	–0.016***	–0.008***
	[5.77]	[5.05]	[4.26]	[0.52]	[6.66]	[3.98]	[5.40]	[3.48]	[10.57]	[5.67]
ebt	0.007***	0.001**	0.007***	0.001***	0.006***	0.002***	0.006***	0.002**	0.006***	0.002***
	[12.17]	[2.45]	[14.83]	[2.80]	[11.80]	[3.84]	[9.65]	[2.52]	[24.73]	[6.13]
*ebt***exp**100	0.007**	0.013***	0.012***	0.015***	0.013***	0.015***	0.004	0.008***	0.009***	0.012***
	[2.44]	[5.68]	[5.29]	[6.95]	[5.40]	[5.73]	[1.49]	[3.46]	[7.53]	[11.21]
Controls	no	yes	no	yes	no	yes	no	yes	no	yes
Observations	15278	15278	15330	15330	13808	13808	11871	11871	56287	56287
R-squared	0.19	0.4	0.27	0.45	0.25	0.44	0.2	0.38	0.46	0.59

Robust *t* statistics in brackets * significant at 10 %; ** significant at 5 %; *** significant at 1 %. Controls are sex, firm size, type of education, professional status and year dummies for IX and X.



*Task set 1: 75 percentile of *kbt* = 22.863 and 25 percentile of *ebt* = 7.896; Task set 2: 50 percentile of *kbt* =1 1.251 and *ebt=25.414;* Task set 3: 25 percentile of *kbt* = 14.112 and 75 percentile of *ebt* = 14.791.

Graphic 1: Experience earnings profiles

All plotted graphs stem from the extended regressions with further controls. The *y*-axis refers to the log monthly wages and the *x*-axis represents the amount of experience. We plotted the graphics for every year separately. We excluded the graphic for the pooled sample but the results are qualitative the same.

The graphics reveal that the rate of depreciation is higher for individuals performing a high share of *knowledge-based tasks* as the profiles of task set 1 peak the earliest in every cross section. For example, in 1979 the wage profile of the first task set peaks at around 24 years of experience whereas the wage profile of task set 2 peaks at around 28 years of experience. Hence, for task set 1 we can say that people with 24 years of experience earn more than for example individuals with 40 years of experience. In contrast we find the maximum of the wage profile for task set 2 four years later with 28 years of work experience. Thus, especially if workers focus on *knowledge-based tasks* they suffer from depreciation and earn less with respect to their younger colleagues.

Moreover, the graphics illustrate that younger workers (i.e., workers of recent vintages) even benefit over workers with other task combinations if they perform mainly *knowledge-based tasks* in their jobs. Thus, for the first years of experience the wage profiles of the first task sets exceed the profiles of the other task sets. However, later in the career the wage paths are exceeded by the wage profiles of task set 2 and task set 3. Especially, the profile of the latter set (i.e., set which has the focus on *experience-based tasks*) shows high wages at the end of careers. Thus, workers of older vintages benefit if they focus on *experience-based tasks.*

6. Conclusion

This paper studies the depreciation processes of different types of skills over a period of more than twenty years. Using four waves of the so-called BIBB / IAB Qualification and Career Survey, we show that two types of tasks must be distinguished: *knowledge-based tasks* demanding technological knowledge and *experience-based tasks* demanding interpersonal skills and characteristic attributes. Making this distinction we can show two important results.

First, the human capital of people performing mainly *knowledge-based tasks* strongly suffers from depreciation, whereas the human capital of people performing *experience-based tasks* does not. Second, workers of recent vintages even benefit if they focus on *knowledge-based task* whereas workers of older vintages benefit if they focus on *experience-based tasks.*

In detail, our results show that the maximum of the observable earnings profiles is attained the earlier the higher the share of *knowledge-based tasks* in a job. In contrast, earnings profiles peak later if the share of *experience based tasks* is higher in a job. Thus, the higher the share of *knowledge-based tasks* the less experienced are the workers with the highest wages. In contrast, the higher the share of *experience-based tasks* the more experienced are the workers receiving the highest wages. Hence, whenever you find many young workers earning more then their older colleagues it indicates that not only the amount of experience plays a role but also the point of time a worker accumulated his human capital (i.e., it is important that the human capital is of recent vintages).

These results can have several implications. First, it is important to separately analyze individual's accumulations of human capital at different stages and career steps. It could be, for example a risky strategy for an individual to only focus on high technological skills throughout his entire career as there is a danger that the individual will be outperformed by younger colleagues at later stages of their career. This could affect the labor market outcomes (wage losses, unemployment) of the individual negatively.

Second, the result could have implications about the age and experience distributions of firms in different industries. Here one could argue that firms in technology intensive industries should stay with high shares of younger workers, whereas firms, for example, in the service sector could benefit from more experienced workers.

References

Arrazola, M. / *de Hevia,* J. (2004): "More on the Estimation of the Capital Depreciation Rate," Applied Economics Letters 11, 145 – 148.

Baltes, P. / *Freund,* A. / *Li,* S. (2005): "The Psychological Science of Human Ageing," in Cambridge Handbook of Age and Ageing, edited by M. L. Johnson, Cambridge, Cambridge University Press, 47 – 71.

Ben-Porath, Y. (1967): "The Production of Human Capital and the Life Cycle of Earnings," Journal of Political Economy 75, 352 – 365.

Compton, D. / *Avet-Compton,* T. / *Bachman,* L. / *Brand,* D. (2003): "Working Memory and Perceptual Speed Mediation of Age-Associated Changes in Cognition within a Sample of Highly-Educated Adults," North American Journal of Psychology 5(3), 451 – 478.

De Grip, A. / *Van Loo,* J. (2002): "The Economics of Skills Obsolescence," in The Economics of Skills Obsolescence: Theoretical Innovations and Empirical Applications, edited by A. De Grip, J. Van Loo, and K. Mayhew, London, Elsevier, 1 – 25.

Groot, W. (1998): "Empirical Estimates of the Rate of Depreciation of Education," Applied Economics Letters 5, 535 – 838.

Laing, D. / *Palivos,* T. / *Wang,* P. (2003): "The Economics of "New Blood", Journal of Economic Theory 112, 106 – 156.

Ludwig, V. / *Pfeiffer,* F. (2005): "Abschreibungen allgemeiner und beruflicher Ausbildungsinhalte," ZEW Discussion Paper No. 05 – 36.

Mincer, J. (1974): "Schooling, Experience and Earnings," New York, Columbia University Press.

Neuman, S. / *Weiss,* A. (1995): "On the Effects of Schooling Vintage on Experience-Earnings Profiles: Theory and Evidence," European Economic Review 39(5), 943 – 955.

Ramirez, J. (2002): "Age and Schooling Vintage Effects on Earnings Profiles in Switzerland," in The Economics of Skills Obsolescence: Theoretical Innovations and Empirical Applications, edited by A. De Grip, J. Van Loo, and K. Mayhew, London, Elsevier, 1 – 25.

Rosen, S. (1975): "Measuring the Obsolescence of Knowledge," in Education, Income and Human Behavior, edited by F. T. Juster, New York, Carnegie Foundation for the Advancement of Teaching & National Bureau of Economic Research, 199 – 232.

– (1976): "A Theory of Life Earnings," The Journal of Political Economics 84(4), 45 – 67.

Skirbekk, V. (2005): "Why Not Start Younger? Implications of the Timing and Duration of Schooling for Fertility, Human Capital, Productivity and Public Pensions," Laxenburg, International Institute for Applied Systems Analysis.

Spitz-Oener, A. (2006): “Technical Change, Job Tasks, and Rising Educational Demands: Looking Outside the Wage Structure,” Journal of Labor Economics 24(2), 235 – 268.

Sternberg, R. / *Grigorenko,* E. (2005): “Intelligence and Wisdom,” in Cambridge Handbook of Age and Ageing, edited by M. L. Johnson, Cambridge, Cambridge University Press, 209 – 21.

Van Loo, J. / *De Grip,* A. (2001): “Skill Obsolescence: Causes and Cures,” International Journal of Manpower 22(1), 121 – 137.

Weiss, Y. / *Lillard,* L. (1978): “Experience, Vintage, and Time Effects in the Growth of Earnings, American Scientists, 1960 – 1970,” Journal of Political Economy 86(3), 427 – 447.

Appendix

Table A1

Descriptive statistics

Variable	**Std. Dev.**	**Mean**	**Max**	**Min**
tasks:				
knowledge based tasks (*kbt*)	7.701	16.604	37.821	3.643
experiecne based tasks (*ebt*)	10.427	16.979	54.375	0.000
ln(monthly wages)	0.448	7.936	9.159	6.551
experience	11.921	18.240	45.000	0.000
sex	0.462	0.309	1.000	0.000
education:				
low education	0.364	0.157	1.000	0.000
medium education	0.436	0.744	1.000	0.000
high education	0.297	0.098	1.000	0.000
firm size:				
less then 5 employees	0.242	0.063	1.000	0.000
5 – 9 employees	0.319	0.115	1.000	0.000
10 – 49 employees	0.435	0.253	1.000	0.000
50 – 99 employees	0.324	0.119	1.000	0.000
100 – 499 employees	0.412	0.216	1.000	0.000
500 – 999 employees	0.256	0.071	1.000	0.000
more then 1000 employees	0.369	0.163	1.000	0.000

Table A2

Tasks for 1979 to 1998

1979

seniority based tasks	knowledge based tasks
Advertising, PR-Work, Publicizing	Researching, analyzing, exploring
Buying, Selling Properties	Projecting, planning, making plans
Parenting, Training, Teaching; Consulting / Counseling	applying and using the law / rights
Negotiating, Representing someone's interests	programming
Publishing, journalistically / literarily working	repairing machines, equipment, vehicles and constructions
Organizing, planning, managing	making constructions, sketching, modeling
Calling for customers, Visiting firms / companies	chemically-physically analyzing and examining
Renting, Brokering Objects	Medically-biologically analyzing and cytologically examining
Auctioning Objects	Shorthanding, ciphering, coding
Serving, Accommodating	Reporting, drawing up the balance sheet
Negotiating with customers / suppliers, Advising customers	Making / Interpreting statistics evaluating data processing working out laws / regulations Examining, appraising, estimating Using, equipping, and maintaining a computer, software, terminals and monitors

1985 / 86

seniority based tasks	knowledge based tasks
Buying, advising, advertising	Researching, analyzing, measuring, examining
Parenting / teaching, training, consulting	making constructions, sketching, designing
Publishing, entertaining, presenting	applying and using the law / rights, registering
Managing, employing personnel	programming
Organizing, planning, managing, leading	equipping machines
entertaining	operating machines
Serving, accommodating	maintaining machines

1991 / 92

seniority based tasks	knowledge based tasks
Buying, selling and advertising	Researching, analyzing, measuring, examining
Teaching, parenting and training	making constructions, sketching, designing
publishing, entertaining, presenting and designing	applying and using the law / rights, registering
coordinating, organizing and planning	programming
Managing, employing personnel	equipping machines
Serving	operating machines maintaining machines

Continued Table A2:

1998 / 99

seniority based tasks	knowledge based tasks
Training and teaching	collecting and processing information
Consulting and providing information	developing and researching
Buying, Selling	repairing
Organizing	guarding and maintaining machines
Negotiating	
marketing	
Serving, accommodating	

Table A3

Job categories

culturist	carpenter, roofer, scaffolder
animal breeder, fishery professions	road and civil engineer
administrator, adviser in agriculture	builder's laborer
agricultural workers, animal	building decorator
horticulturist	interior decorator, upholsterer
forest and hunting professions	cabinetmaker, model maker
miners	painter, varnisher and related occupations
mineral, petroleum and petroleum gas production	goods examiner, transport dressing
mineral processing	unskilled worker
brick machining	machinist and related occupations
construction material manufacturer	engineer
ceramist	chemist, physicist, mathematician
gaffer	technician
chemical worker	technical specialist
synthetical fabricator	goods merchants
paper manufacturer, paper fabricator	bank and insurance employee
pressman	other service occupations and related occupations
wood preparation, wood fabrication	occupations for ground transport
metal manufacturer, roller	occupations for sea and air transport
former, caster	occupations for communication
metal forming (non-machining)	chief storekeeper, storekeeper, transport worker
metal forming (machining)	entrepreneur, promoter, auditor
metal surface machining, quenching and tempering	delegate, important administrative occupations
metal binder	accounting clerk, data processing specialist
forger	office clerks, office hand
fitter	security services
locksmith	jailer
machanician	registrar

Continued Table A3:

toolmaker	publicist, interpreter, librarian
metalworker and related occupations	artist and related occupations
electrician	doctor, pharmacist
assembling and metal occupations	remaining occupations of health care
spinning occupations	social worker and related occupations
textile manufacturer	teacher
textile fabricator	humanities and social science occupations
textile refiner	pastor
leather manufacturer, leather and fur fabricator	personal hygiene
backery, confectioner	guest attendant
meat and fish fabricator	housekeeping occupations
food preparation	cleaner
beverage and stimulants manufacturer	
remaining nutrition occupations	
bricklayer, concrete worker	