ELSEVIER European Economic Review 39 (1995) 943–955

EUROPEAN ECONOMIC REVIEW

On the effects of schooling vintage on experience–earnings profiles: Theory and evidence [1]

Shoshana Neuman, Avi Weiss *

Department of Economics, Bar-Ilan University, 52900 Ramat-Gan, Israel

Received October 1991, final version received March 1994

Abstract

In this paper a distinction is made between human capital depreciation related to a worker's aging and depreciation due to the obsolescence of the worker's education. Schooling-specific obsolescence of human capital is incorporated in the Mincerian model of earnings, and it is shown how this obsolescence affects the worker's earnings profile. Using the Israeli 1983 Census we show that for 'high-tech' oriented industries (for which obsolescence is relatively important) obsolescence effects are more significant than for 'low-tech' oriented industries, and, consequently, the experience–earnings peak falls faster with increasing education in the former.

Keywords: Human capital; Obsolescence; Depreciation; Vintage; Experience–earnings profiles

JEL classification: J31; J24

1. Introduction

Age–earnings profiles have been studied continuously for over 25 years. Among the many implications of the human capital models on which these studies

* Corresponding author.

[1] We would like to thank Christopher Flinn, Julian Silk, the referees and the editor for their very helpful comments. All remaining errors are the sole responsibility of the authors.

SSDI 0014-2921(94)00019-V

are based is the (theoretical and empirical) finding that earnings over the life-cycle peak at some age, and the more educated an individual the later the earnings peak (see, e.g., Becker (1964)). This means that differences between the earnings of workers with different levels of education rise with age. These findings are based on (among other things) the combination of the accumulation of human capital even after formal schooling ends, the depreciation of all capital over time, and the fact that the more educated start work at a later age.

The second of these effects – depreciation – can be broken down into two major types: internal depreciation and external depreciation. Internal depreciation, which is implicitly assumed in most studies, is the depreciation attributable to the worker. This includes the loss of physical ability as well as any loss of mental capacity. External depreciation is that caused by external forces, i.e., it is the lowering of the value of a worker in the market due to changes in the environment. In particular, one element of these external forces is the gradual obsolescence over time of the stock of knowledge obtained during the schooling process. This is due to so-called 'vintage' effects. (See, e.g. Becker (1964) and van Imhoff (1988).) Rosen (1975) and Weiss and Lillard (1978) argue that it is impossible to disentangle obsolescence of human capital from its (internal) depreciation since newer vintages enter and the worker gets older simultaneously.

Mincer (1974) changed the emphasis from age to labor market experience, claiming that on-the-job investment is better indexed by market exposure than by age. Mincer estimated experience as age minus schooling minus six (the age at which schooling begins) and this has become widely used in empirical research on male earnings. One of his findings is that when experience is used instead of age, the shift of the earnings peak with schooling disappears. Instead, earnings profiles tend to be parallel, with the better educated simply receiving higher wages at all levels of experience.

In this paper we too 'Mincer' our theory (a term used by Rosen (1992)) by extending Mincer's model to include human-capital depreciation that is schooling-specific. In particular, we show how schooling vintage can affect experience–earnings profiles. We show that, under the assumption that, on average, vintage effects are more important for more highly educated people, the effect of education on the earnings peak is reversed – more highly educated individual's earnings peak at lower levels of experience. Thus, wage differentials actually decrease with experience. These effects may manifest themselves to different extents in different industries, so that if (internal) depreciation is the same across industries (since it may be dependent on the worker and not on the industry), it may be possible to disentangle the two types of depreciation. This suggests that in studies related to the experience–earnings relationship it may be improper to group together people from different industries without properly controlling for different vintage effects.

We test our hypothesis by using 'Mincer-type' equations and focusing on the experience level at which earnings peak for cross-sectional data (where peaks are generally found to exist). In studies using panel data, in which peaks are generally not found, the hypothesis continues to hold, however the focus would have to be on the decreasing differences in earnings with increases in experience. To this end, we also show how the standard Mincerian wage equation should be altered to account for this phenomenon.

The paper proceeds as follows. Mincer's model is extended in Section 2 to include schooling specific depreciation, and our hypothesis is discussed. Section 3 presents a simple graphical exposition of the theory. Section 4 discusses the data used to test the theory and the way the model is tested, and Section 5 reports the results of the tests. A brief summary concludes the paper.

2. The model

As shown in Mincer (1974), after j years in the labor force, an individual's earnings capacity, E_j, will be approximately

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

where E_0 is his earnings capacity (or gross earnings) when he starts working, i.e., after graduating from school; $k_t = C_t/E_t$ is the ratio of investment in on-the-job training (C_t) to gross earnings (E_t) in period t; and r_t is the rate of return on the investment of C_t. It is assumed that $k_t \leqslant 1$ and declines over time.

To accommodate the existence of human capital depreciation in the model, Eq. (1) is amended by positing a rate δ_t at which the human capital stock, and hence E_t, depreciates in time period t. Denoting by $k_t^* = C_t^*/E_t$ the ratio of gross investment C_t^*, to earnings capacity, and by $k_t = C_t/E_t$ the ratio of net investment C_t to earnings capacity, Eq. (1) becomes

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

Our focus is on earnings peaks, namely the level of experience at which earnings reach a maximum. The peak of earnings capacity (E_j) is reached when $k_j = 0$, i.e., when $k_j^* = \delta_j/r_j$. Gross investment is still positive at this point, but net investment is zero.

Since empirical data on observed earnings correspond more closely to net earnings than to earnings capacity, Eq. (2) must be amended. [2] Net earnings, Y_j,

[2] Y_j – net earnings – would equal observed earnings as they are usually reported if C_j consisted of opportunity costs only. However, since direct costs are much smaller than opportunity costs, observed earnings more closely approximate Y_j than E_j.

are given by $Y_j = E_j - C_j^* = E_j(1 - k_j^*)$, which, together with Eq. (2) yields

$$\ln Y_j = \ln Y_{j-1} + \ln\left(1 + r_{j-1}k_{j-1}^* - \delta_{j-1}\right) + \ln\left(1 - k_j^*\right) - \ln\left(1 - k_{j-1}^*\right), \qquad \text{(Mincer, Eq. 1.23)} \tag{3}$$

so that observed earnings peak approximately when

$$\delta_{j-1} = \left(1 + r_{j-1}\right)k_{j-1}^* - k_j^*. \qquad \text{(Mincer, p. 21, fn. 10)} \tag{4}$$

k^*, the gross investment ratio, can be expected to monotonically decline over a worker's work-life, so that

$$k_t^* = k_0^* \phi(t), \tag{5}$$

where k_0^* is the gross investment ratio during the first year of work, t is the number of years of experience, and $\phi(t)$ describes the pattern of decline, with $\phi'(t) < 0$.

Any of the underlying variables may vary with the level of schooling, so that individuals with different schooling attainments may have different earnings profiles. Since we focus on schooling-specific depreciation we will assume for now that r, k_0^* and ϕ are not dependent on the level of schooling.

There are assumed to be two different types of depreciation. The first is a function of a person aging, which includes a lessening of physical and mental prowess. This depreciation is assumed, for simplicity's sake, to operate similarly for workers with different levels of education. The second type of depreciation is dependent on the level of schooling the worker has obtained, and is a measure of how outdated his education has become. It seems reasonable to assume that an elementary school graduate's human capital does not suffer much from obsolescence since the material taught in elementary schools has not changed much over time. However, an electrical engineer who was trained 20 years ago learned vastly different material than one who just finished his schooling. Or, for example, today's high school student learns computers, something that was not taught even 10 years ago. Thus, a 12 year education today and a 12 year education 10 years ago are vastly different and should not necessarily be lumped together. For these reasons we assume that the older the human capital the more obsolete it becomes, and the higher the level of education the more quickly the capital becomes obsolete, i.e., $\delta'_{j-1}(S) > 0$, where S is the level of schooling.[3]

Substituting Eq. (5) into Eq. (4), earnings peak when

$$\delta_{j-1}(S) = k_0^*\left[\left(1 + r_{j-1}\right)\phi(j-1) - \phi(j)\right]. \tag{6}$$

Since $\delta'_{j-1}(S) > 0$ and $\phi'(t) < 0$, the level of experience at which net earnings

[3] The rate of depreciation, however, may differ in different types of industries. This idea is developed further in Section 4.

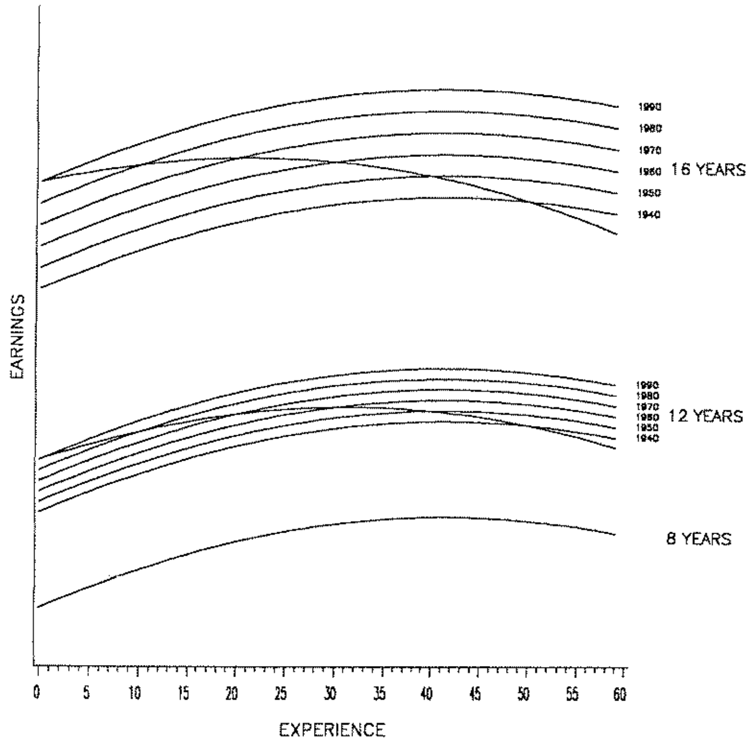

Fig. 1. The effect of schooling vintage on experience–earnings profiles.

peak decreases with S, i.e., other things being equal workers with higher education will have their earnings peak at earlier stages of labor market life. [4]

If r, k_0^* or $\phi(t)$ do vary with schooling, then the conclusion is not always clear. For example, if $k_0^{*\prime}(S) < 0$. i.e., more educated workers invest less on-the-job right after formal schooling is finished, then our previous result is strengthened – the level of experience at which net earnings peak decreases with schooling even faster. However, if $k_0^{*\prime}(S) > 0$ so that the more educated also invest more on-the-job, then the level of experience at which earnings peak decreases with schooling only if δ_{j-1} increases faster with S than k_0^* does. Similar considerations hold for r and $\phi(t)$.

[4] Clearly the same cannot be said about the *age* at which earnings peak, since experience is defined as age – schooling – 6.

3. A graphical representation

To clarify the arguments made herein, we present a graphical illustration of the problem. In Fig. 1 we plot three series of experience–earnings profiles assuming for each that earnings have a peak. [5] The uppermost series is for people with 16 years of schooling, the middle series is for people with 12 years of schooling, and the bottom curve is for people with 8 years of schooling. Each curve depicts the experience–earnings profile of a worker given that he does not experience any obsolescence of his capital, i.e., it is the profile for a certain time-equivalent level of schooling. The peak of each curve is assumed to be the same for everyone, so that none of the variables discussed in the last Section are affected by schooling. The year shown on each curve is the year in which schooling was completed. Assume it is currently 1990. Taking, for example, college graduates, those that just graduated will be on the uppermost curve marked 1990. In the absence of vintage effects someone who finished schooling in 1980 would also be on the same curve, but because of vintage effects he is on a lower curve since *his* 16 years of schooling is equivalent to someone with less than 16 years of schooling who just left college. Again, the 1980 graduate would stay on the curve he is presently on in the absence of any *further* depreciation of his human capital. However, given further depreciation he will be on the 1970 curve 10 years from now (assuming the rate of obsolescence is time invariant).

When plotting an experience–earnings profile from a cross-sectional data set, we would find the people just entering the market on the 1990 curve, those with 10 years of experience on the 1980 curve, etc. Drawing a curve through these points (the dark lines in Fig. 1) we get a profile that rises slower, peaks earlier and falls faster than in the absence of obsolescence. The same relationships hold for high school graduates, however the rate of obsolescence is assumed to be smaller, so the changes are not as drastic. For elementary school graduates we assume in Fig. 1 that there are no vintage effects so that nothing shifts – these workers move along the curve.

As shown, the shift in the peak is smaller for less educated workers, so the earnings peak shifts to the left with an increase in schooling, and the earnings curves for the different education level groups converge. If other factors affect the peaks of the earnings profiles, this vintage effect may be less obvious, as discussed at the end of the last section.

[5] While we assumed that earnings have a peak, which is found in cross-sectional studies, panel data studies suggest that earnings are monotonically increasing. The difference is often attributed to a diminishing supply of labor in the latter parts of one's work-life. This common problem does not plague our study since we use only full-time employees in our empirical analysis. However, monotonically increasing profiles for panel data studies can be reconciled with non-monotonic cross-sectional profiles by considering the growth in the real wages of workers over time – in panel studies this growth will show that income rises monotonically with experience, but in cross-sections, where growth is not reflected, the older workers receive lower salaries than the younger workers.

4. Data and methodology

As discussed at the end of Section 2, if variables other than depreciation vary with the level of education, our theory does not predict how the peak of the earnings profile will shift with schooling. Thus, simply showing that peaks shift to the left as schooling rises is neither necessary nor sufficient (the latter since the peak could shift to the left for other reasons). In order to properly test the hypothesis we need to differentiate between two groups, such that in one group obsolescence is a major factor, while in the other it is not, and show that the peaks shift *more* for the group with the stronger vintage effects. [6] For this purpose we use a distinction based on an empirical analysis conducted by Bregman et al. (1989). In their study they use a sample of 670 manufacturing firms in Israel in 1982, and test to see how technologically oriented each firm is. They characterize 'high-tech' firms by using a 'High-Tech Indicator' composed of three factors: the technical quality of labor – i.e., the proportion of engineers and technicians in the labor force; the quality of capital – i.e., the proportion of capital that is less than 6 years old; and an index of Research and Development activity. Once this is done, they categorize the firms by industry and calculate what percentage of production is produced by 'high-tech' firms in each industry.

For our purposes we divided the industries into those in which more than 50% of production is produced by high-tech firms, and which are therefore considered high-tech oriented, those in which a third or less of the production is produced by high-tech firms (which we call low-tech industries), and all others which were not included in our analysis. The first group includes workers in the branches of Electronics and Transport Equipment (79% of production produced by high-tech firms), Chemicals and Minerals (60%) and Metals (55%). The 'low-tech' group includes Textiles and Clothing (8%), Light Industries (wood, paper, printing, rubber and plastics – 17%) and Food, Beverages and Tobacco (33%). See Bregman et al. (1989, Table 7, p. 26).

While it would have been preferable to classify the industries by a measure of technological *change*, such as investments in Research and Development, rather than by the measure of technology that we are using, these data were not readily available from Bregman et al. Fortunately there is a strong positive correlation between the two measures – 94% of the total investment in Research and Development (in 1982) was done in high-tech firms, only 0.2% in low-tech firms, and the rest – 6% – in medium-tech firms (Bregman et al., 1989, Table 5, p. 25).

[6] While Weiss and Lillard (1978) suggest that changing market conditions (and not necessarily obsolescence) can be responsible for different rates of return to different vintages, these changing market conditions cannot explain the differences between the workers in our two groups. This is because there is no a priori reason to assume that conditions differ in our two industry groups (defined below). Since there is no reason to believe that workers in the different industries don't face the same basic conditions (in terms of schooling decisions), we conclude that the remaining differences are related to obsolescence.

Therefore, our 'high-tech' industries can be considered 'high technological change' industries as well.

Data for married Jewish males, 21–65 years of age, who work full time in Manufacturing and receive a salary were taken from the 20% questionnaire of the 1983 Census of Housing and Population conducted by the Israeli Bureau of Statistics. We use only Manufacturing since this is the only part of the economy for which Bregman et al. (1989) made the distinction. We were left with a sample of 12,444 high-tech workers and 7,305 low-tech workers. The characteristics of the two groups are summarized in Table 1, which shows that high-tech workers tend to be younger (less experienced), better educated, and more highly concentrated in scientific and professional occupations.

We calculated experience–earnings profiles for each group based on a regression in which the ln of monthly earnings was regressed on the ln of hours of work per week, the ln of weeks of work per year, ethnic origin (western vs. non-western), years residing in Israel, occupation dummies, [7] experience (*exp*), and experience squared (*expsq*).

The equations were run separately for each education level (0–8, 9–11, 12, 13–16 and 17 + years of schooling), and for high-tech and low-tech employees separately. High school graduates were separated since, in studies using U.S. data, they have been seen to exhibit different earnings patterns from workers with 9–11 years of education. This pattern should hold even more strongly in Israel where the financial cost of going to high school is very low, so that high school dropouts are likely to have vastly different productive capacities than do high school graduates.

In addition, a single regression was run for all of the data with the additional variables schooling (*sch*) and experience times schooling (*expsch*) included. In addition, a dummy term for high-tech (*h*) was included as were interaction terms of high-tech with experience (*hexp*), experience squared (*hexpsq*), schooling (*hsch*) and experience times schooling (*hexpsch*). Obviously this approach places restrictions on the coefficients of the non-interacted variables, but it allows us to show how the usual earnings equation is modified to account for this obsolescence. The *expsch* variable is not usually included in earnings studies and is the focus of our analysis. This variable shows how the return to increased experience changes with increased schooling. Our main hypothesis is that the coefficient on *hexpsch* will be negative showing that this return depreciates faster in high-tech than in low-tech industries. Note that in this setting the focus is no longer on the peak, but rather on the shift in the profile. This makes this approach more appropriate for panel studies where peaks may not be found.

[7] The occupation of the worker was introduced using a series of dummy variables relating to occupation: scientific and academic workers, other professional and technical workers, managers, clerical workers, sales workers, service workers, skilled workers and unskilled workers, with agricultural workers serving as the reference group. All regressions were also run without the occupation dummies, with no qualitative change in results.

5. Main findings

Experience–earnings profiles derived from the separate earnings regressions are plotted in Fig. 2. As seen, workers in high-tech oriented branches have higher earnings than similarly educated individuals in the low-tech branches. This relationship holds for all education levels and almost all experience levels. In addition, the gap increases as the education level rises. We attempted to explain

Table 1
Sample characteristics, male, Jewish, married, full-time, 21–65 year old, salaried workers

Variables	High-tech workers		Low-tech workers	
	Mean (frequency)	Standard deviation	Mean (frequency)	Standard deviation
Monthly income (ln)	10.553	0.661	10.245	0.628
Hours worked per week	47.907	5.874	48.945	6.698
Weeks worked per year	50.564	6.066	50.257	6.600
Years of schooling:				
0–8 years	0.213		0.388	
9–11 years	0.285		0.290	
12 years	0.178		0.165	
13–16 years	0.235		0.122	
17 + years	0.088		0.035	
Experience groups:				
0–10	0.164		0.099	
11–20	0.393		0.275	
21–30	0.194		0.189	
31–40	0.146		0.204	
41 +	0.104		0.233	
Period of immigration:				
Before 1947 or Israeli born	0.377		0.315	
1948–1965	0.432		0.504	
1965–1971	0.069		0.070	
1972 +	0.122		0.111	
Oriental ethnic origin	0.195		0.251	
Occupation:				
Scien. and academic workers	0.100		0.017	
Prof. and technical workers	0.129		0.044	
Managers	0.089		0.084	
Clerical workers	0.077		0.080	
Sales workers	0.021		0.033	
Service workers	0.016		0.026	
Skilled workers	0.518		0.584	
Unskilled workers	0.049		0.126	
Agricultural workers	0.001		0.006	

Source: Israeli Census of Population and Housing, 1983.

this difference by correcting for the different occupational and ethnic mix of the groups, but were unable to explain more than 20% of the difference in this manner. Thus, the remaining difference must be related to unmeasured heterogeneities between workers, which we assume are unrelated to the variable of interest.

The experience–earnings profiles for both the high-tech and the low-tech industries have the usual concave shapes found in cross-sectional studies, with the profiles being higher and steeper the higher the educational attainment. The drastic shape change for low-tech workers with post-graduate levels of schooling may be the result of the relatively small number of observations in that group. The experience levels at which earnings peak in Fig. 2, which are of particular interest here, decrease with schooling in both the low-tech and high-tech industries, but the peaks in the high-tech industries decrease much faster, as shown in Columns 4 and 5 of Table 2. In fact, while for the lowest education group low-tech workers' earnings peak 2.5 years earlier than they do for high-tech workers, for the highest education group low-tech workers' earnings peak 2.7 years later than they do for high-tech workers. [8] In addition, as predicted, earnings converge at more advanced levels of experience.

In order to test whether the differences in the peaks are significant, we used the 'delta method' to construct standard errors for each peak. [9] We assumed that the populations were the same, and estimated the coefficients from our earnings equation for each schooling group without differentiating between high-tech and low-tech workers. [10] The peak was then constructed and standard errors were calculated for the peak. A t-test was carried out to see whether the peaks for high-tech and low-tech were significantly different. As shown in Table 2, the means were different for all but one schooling group, and, in fact, the difference was significant both when the peak was greater for low-tech workers and when it was greater for high-tech workers.

In order to show how this argument is incorporated into the usual earnings

[8] Strictly speaking, our model predicts that the peak for high-tech workers should be at lower levels of experience than the peak for low-tech workers for all schooling groups. The fact that this is not so for the low education groups suggests that the model is not rich enough to pick up some inter-group differences. Additional assumptions regarding some of the parameters would be necessary to address this point. However, for purposes of our study we focus on the differences between intra-group peak shifts in high-tech and low-tech industry categories, and not on differences between these industries for each schooling level, so the aforementioned inconsistency with the theoretical model is of minor significance.

[9] Variances were estimated using the formula in Mood, Graybill and Boes (1974, p. 181), which is analogous to the delta method.

[10] However, a different intercept was allowed for by including a dummy for high-tech workers. This was done because of the different levels of the profiles in Fig. 2.

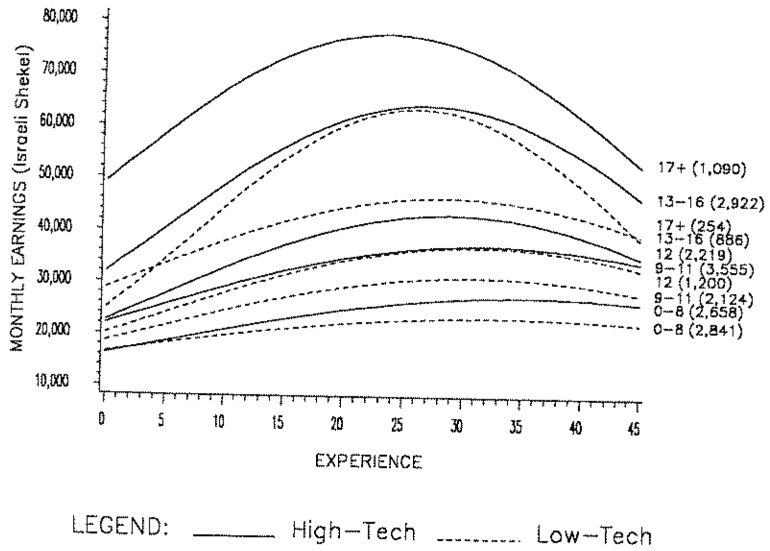

Fig. 2. Experience–earnings profiles by education level; High-tech and low-tech industries. *Source:* Tapes of the 1983 Israeli Census of Population and Housing. *Notes:* Male, Jewish, married, full-time, 21–65 year-old, salaried workers. Number of observations in parentheses.

equation, we ran one regression using all of the data, as discussed in Section 4. The results were:

$$\begin{aligned}\ln Y = {} & \underset{(37.14)}{6.433} + \underset{(10.57)}{0.039} * exp - \underset{(-10.10)}{0.00047} * expsq + \underset{(14.58)}{0.073} * sch - \underset{(-5.66)}{0.00084} * expsch \\ & - \underset{(-2.40)}{0.215} * h + \underset{(3.37)}{0.016} * hexp - \underset{(-2.98)}{0.00018} * hexpsq + \underset{(3.79)}{0.022} * hsch \\ & - \underset{(-2.32)}{0.00044} * hexpsch + X\beta + \epsilon.\end{aligned} \tag{7}$$

Table 2
Years of experience at which earnings peak

Schooling	All workers		Low-tech	High-tech	t-static
	Mean	Standard deviation			
0–8	34.4	0.756	33.2	35.7	3.31*
9–11	31.3	0.848	31.2	31.9	0.83
12	29.5	0.797	31.3	28.9	−3.01*
13–16	27.0	0.714	28.5	26.8	−2.38*
17+	24.0	1.346	26.1	23.4	−2.01*

Note: The column '*t*-statistic' tests whether the difference between the peaks for high-tech and low-tech are significant using the standard deviation of the peak derived from the variance–covariance matrix of the regression for all workers. An asterisk denotes statistical significance at the 5% level.

t-statistics are reported in parentheses. The X matrix contains all of the other variables discussed above. As expected, income increases with experience but at a decreasing rate, and it also increases with schooling. Not surprisingly experience and education have higher payoffs in high-tech than in low-tech industries, thus capturing the heterogeneity between the workers. Note that the coefficient on the high-tech intercept is negative, so that once the different pay for schooling and education are taken into account we no longer see higher profiles for high-tech workers. The coefficients of interest – *expsch* and *hexpsch* – are both negative. This means that there is greater depreciation in the return to experience for the better educated in both industries, but this depreciation is more significant for high-tech than for low-tech workers. This final result confirms our hypothesis, and shows how to account for this type of depreciation. [11]

6. Summary and discussion

In this paper we differentiated between depreciation in human capital related to a worker's aging and depreciation due to the obsolescence of the older worker's education. The presence of schooling-specific obsolescence of human capital was incorporated in the Mincerian model of earnings and it was shown how this obsolescence affects the worker's earnings profile. Unlike in Rosen (1975) and Weiss and Lillard (1978) we suggest that these two types of depreciation can be separated if a variable can be found that affects the latter but not the former. To this end, we stipulated that the human capital in certain types of industries is more

[11] Depreciation in our model could be broken up as follows: $\delta = \delta_0 + \delta_s S(1 + \delta_h h)$, where S is the level of schooling and h is a dummy variable for high-tech industries, δ_0, δ_s, $\delta_h > 0$. In Eq. (7) the coefficient on *expsch* could be interpreted as δ_s if the only reason experience is less valuable for more highly educated workers is because their human capital depreciates faster. (An alternative interpretation is that experience is simply less relevant for more highly educated workers because they already come with all the tools they need. This interpretation is less palatable since it is generally believed that the higher the level of education, the more experience adds to productivity. This is one of the reasons given for the finding that experience–earnings profiles are steeper for the more educated. If, indeed, more educated workers benefit more from experience, then δ_s is larger than measured by this coefficient.) By similar reasoning, the coefficient on *hexpsch* could be interpreted as $\delta_s \delta_h$. (This interpretation is less problematic since there is no reason to expect experience to be less important in the high-tech industries than in the low-tech industries for workers with the same level of education. To the extent that the opposite is true, this coefficient understates the importance of this obsolescence.) Under these assumptions we find that $\delta_s = 0.00084$ and that $\delta_s \delta_h = 0.00044$, so that $\delta_h = 0.52$. No direct estimate of δ_0 is available using a quadratic specification. However, if we add assumptions about the interest rate and the length of the work life, the model can be manipulated to yield a reasonable estimate of δ_0. For example, given our finding of an earnings peak at approximately 30 years of experience, if we assume that $r = 0.08$ and that the average work-life is 40 years, we find that $\delta_0 = 0.0268$. We would like to thank the referee for suggesting this interpretation and for recommending that we present estimates of these components of the depreciation rate.

subject to obsolescence effects than in others, but that other human capital depreciation is not systematically different between these two types of industries. Using the Israeli 1983 Census we separated between 'high-tech' and 'low-tech' oriented industries and showed that for the group for which obsolescence is relatively important these obsolescence effects are more significant. Particular emphasis was placed on the peak of the earnings function (which is usually found in cross-sectional studies) and it was shown that the peak falls faster for those in industries where obsolescence is more of a factor (high-tech industries). In addition, we showed how the standard Mincerian wage equation should be altered to account for this phenomenon.

Cross-national evidence would contribute significantly to the robustness of our suggested theory and empirical findings. We hypothesize that the more human capital rich and technologically oriented is the country the larger will be the life-cycle differences between experience–earnings profiles of workers in 'high-tech' versus 'low-tech' industries. Thus, for example, such a distinction would be important for countries like Israel where natural resources are scarce and two of the resources contributing most significantly to production are human capital and technology.

In addition, studies of a single economy over time would provide useful tests, particularly if technological changes over the period were significant. Israel, again, may be a good example, since the massive Russian immigration currently underway is comprised largely of immigrants with high educational attainments (more than half of them are college graduates) concentrated mainly in technologically oriented professions. Thus, significant structural and technological changes can be expected in the near future.

References

Becker, Gary S., 1964, Human capital (National Bureau of Economic Research, New York).

Bregman, Arie, Melvyn Fuss and Haim Regev, 1989, High-tech firms in Israeli industry, Discussion paper 89.04 (Bank of Israel, Jerusalem).

Mincer, Jacob, 1974, Schooling, experience and earnings (Columbia University Press for the National Bureau of Economic Research, New York).

Mood, Alexander M., Franklin A. Graybill and Duane C. Boes, 1974, Introduction to the theory of statistics, Third edition (McGraw-Hill, New York).

Rosen, Sherwin, 1975, Measuring the obsolescence of knowledge, in: F. Thomas Juster, ed., Education, income and human behavior (McGraw-Hill, New York).

Rosen, Sherwin, 1992, Distinguished fellow: Mincering labor economics, Journal of Economic Perspectives 6, 157–170.

van Imhoff, Evert, 1988, Age structure, education, and the transmission of technical change, Journal of Population Economics 1, 167–181.

Weiss, Yoram and Lee A. Lillard, 1978, Experience, vintage and time effects in the growth of earnings: American scientists, 1960–1970, Journal of Political Economy 86, 427–447.