NBER WORKING PAPER SERIES

Educational Screening and Occupational Earnings

Edward N. Wolff
and
Joel Hay

Working Paper No. 174

NATIONAL BUREAU OF ECONOMIC RESEARCH, INC.
261 Madison Avenue
New York, N.Y. 10016

April 1977

Preliminary; Not for Quotation

Abstract

The educational screening hypothesis states that beyond a certain point schooling functions as a signalling device to identify pre-existing talents. We test for the presence of screening by comparing the schooling and earnings of self-employed workers and of those employed by others in a sample set of occupations. We expect those employed by others to pursue additional schooling to signal prospective employers. We expect self-employed managers to acquire no additional schooling for signalling purposes. We expect other self-employed workers to obtain additional schooling to signal potential customers. Our empirical results, based on 1970 Census data, strongly support the case for screening. However, the relative magnitude of the screening portion of schooling is relatively modest, lying between approximately 5 and 10 percent.

Educational Screening and Occupational Earnings*

The educational screening hypothesis has received considerable attention in recent years. Simply stated, it is that beyond a certain point schooling does not improve an individual's productive capacity but instead functions as a signalling device to identify his pre-existing talents.[1] A prospective employer who has no direct way of assessing an applicant's productive capabilities uses his educational attainment level as an indicator of his expected productivity. Employers therefore pay more to the more highly educated applicants (or hire them in favor of less educated applicants), not because (or solely because) education enhances their productivity but because it identifies the more productive workers. A necessary corollary of this, as Spence (1973) argues, is that for the job market to remain in equilibrium, the more educated will in fact have to demonstrate their greater productivity on the job. The observed positive relation between schooling and earnings is then due to the identification or screening function of education, rather than to a productivity-augmenting process.

---

*This paper was originally presented at an NBER seminar in Stanford in March 1977. We would like to thank those present for their comments and Robert Lipsey for his helpful suggestions. The work for this paper was supported by the National Science Foundation, Grant No. SOC74-21391.

[1]As Wolpin (1975) points out, it is not necessary to assume that there is no productivity effect from schooling, only that beyond a certain level of schooling the effect is signalling and not productivity augmentation.

(See Spence (1973), Arrow (1973), Layard and Psacharopoulos (1974), Albrecht (1974), Stiglitz (1975), Wolpin (1975), and Riley (undated) for variants on this basic argument.)

Empirical attempts at verifying the presence of screening have to date either been misformulated, negative or inconclusive. Taubman and Wales (1973) present one of the earliest tests of screening. Using data from the NBER-Thorndyke sample, they estimate earnings functions for each of seven occupational groups by regressing earnings on schooling, age, ability (as measured by the Aviation Cadet Qualifying Test), and other socio-demographic variables. These earnings regressions are then used to predict an individual's expected earnings, had he been employed in another occupation. Finding that a large percentage of blue-collar workers earn less than their expected income in white-collar and other occupations with higher educational requirements, they conclude that education acts as a barrier to entry in these occupations. The weakness of the Taubman and Wales test is that they assume that the only characteristics that affect worker productivity are the variables they use in their earnings regression. In fact, these explain only a small part of the variance in earnings. If there are unobserved traits positively associated with schooling (perhaps initiative, for example) and positively correlated with earnings, then the Taubman and Wales test only begs the question: Does schooling produce these productivity-related traits like initiative and thus augment productivity or do individuals with more (innate) initiative pursue more education, in which case schooling screens these traits? The Taubman and Wales test is thus inconclusive. (See Wolpin and Riley for related criticisms.)

Layard and Psacharopoulos propose three hypotheses for testing the presence of screening. First, the rate of return to uncompleted courses should be lower than that to completed ones. Second, standardized educational differentials in earnings should not rise with age, since employers should have better information about older employees' abilities. Third, if screening is the main function of education, there are alternative testing procedures that can be done more cheaply than schooling. None of these hypotheses was empirically confirmed. However, none of these propositions is implied by the screening hypothesis. The first is really a "credential" or "sheepskin" hypothesis that a diploma per se is used as a screening device, rather than years of education.[2] The second hypothesis also does not follow from the screening hypothesis. All that the screening hypothesis contends is that schooling itself does not increase worker productivity. In fact, higher educated individuals may be more productive and must be, as Spence argues, for the job market to remain in equilibrium. Therefore, there is no necessary reason for earnings differentials between schooling groups not to increase with age. The third hypothesis is irrelevant to the argument, since the existence of cheaper alternative testing devices does not contradict a screening function of schooling.

Albrecht's test was to compare the success of applicants for a

---

[2]Eckaus (1973a) finds similar refutation for the sheepskin hypothesis. When adjusted for hours worked, college graduates have the same rate of return to schooling relative to college drop-outs as college drop-outs do relative to high school graduates.

given position of those inside an organization with those outside the organization. His data were applicants for the position of tax auditor for an Internal Revenue Service office in San Francisco. He reasoned that the office would have better information on inside candidates than outside ones. Therefore, if education were used as a screening device, schooling should have less bearing on the hiring decisions of inside applicants than outside ones. This hypothesis was not confirmed. But here too the inference is not warranted. Education may be directly (though not causally) related to an individual's on-the-job productivity and still be used as a screening device. Albrecht's results thus do not refute the screening hypothesis.

Using data on college graduates working in a large corporation, Wise (1975) found that earnings were significantly related to the undergraduate grade point average (GPA). Moreover, when college quality (selectivity) was controlled for, GPA was still significant. In fact, earnings increased faster with GPA at the more selective than less selective colleges. On this basis, Wise concluded that "college education is not only a signal of productive ability, but in fact enhances this ability." Again, the conclusion is not warranted by the results. From Wise's findings, one could alternatively argue that a sophisticated employer like a large corporation uses not only schooling level but college quality and academic achievement to screen employees, because innate ability is better identified by these three factors than by schooling level alone. Moreover, the fact that earnings rise faster with GPA at more selective colleges suggests that the

difference between an A and a B at a more selective school represents a greater spread in ability than at a less selective school (also, see Lazear (1977)).

Wolpin presents the most direct test of the screening hypothesis to date. Using the NBER-Thorndyke sample, he estimated separate earnings equations for salaried and self-employed workers, where the explanatory variables are schooling, experience, and ability. His reasoning is that students planning to go into their own business will acquire less schooling than those planning to work for an employer, since the former will stay in school only long enough to satisfy the needs of their work, whereas the latter will acquire additional schooling to signal a prospective employer. Wolpin makes four predictions based on the screening hypothesis. First, self-employed workers will have a lower mean schooling than salaried workers. Second, the increment in earnings from schooling will be lower for self-employed than salaried. Third, earnings differentials between schooling classes will decline with experience for salaried workers. Fourth, earnings profiles by schooling class will diverge with experience for self-employed workers. None of these hypotheses was empirically confirmed.

Wolpin's procedure avoids the basic objection to the previous tests that productivity (and hence earnings) should be positively related to schooling, irrespective of whether schooling augments productivity or functions as a screening device. However, there are other problems with his tests. First, mean schooling for self-employed should be lower than that of salaried workers only if the occupational mixes are substantially the same. In fact, self-employed workers are

concentrated in occupations requiring more schooling (see below). In addition, there is reason to believe that in many occupations self-employed workers will acquire more schooling than their salaried counterparts to signal prospective clients (see below). Second, the return to schooling should, in fact, be greater for self-employed than salaried workers. The reason is that self-employed workers (given perfect foresight) acquire only as much schooling as needed in their occupation. Given the same ability (or distribution of ability), self-employed workers should receive the same earnings as salaried workers with more schooling. (See Riley for a slightly different argument.) Third, as we argued above, there is no reason why age-earnings profiles by schooling class should converge with age for salaried workers, even if screening takes place. Fourth, inversely, there is no reason why the profile should diverge with age for self-employed workers.

Riley proposes a test of screening though in the paper shows no empirical results. He argues that in some occupations the direct observation of an individual's productivity and potential is more difficult than in other occupations. Therefore, screening would more likely occur in the former than in the latter occupations. One should therefore observe a lower rate of return to schooling in the screened than in the unscreened occupation. Moreover, in the screened occupations, education credentials are by definition the basis of the initial wage offer. Therefore, an earnings function should be a better predictor of earnings in earlier than in later years for screened jobs, and the predictive power of the earnings function should decline in

the screened relative to the unscreened sector with experience. The problem with this approach is that no independent means is provided of distinguishing between screened and unscreened occupations, except by whether or not it fulfills the prediction.

I. An Alternative Screening Test

In this paper we shall present a new formulation of a screening test. We shall then test for the presence of screening using data from the 1970 Census Public Use Sample. Our results generally confirm the presence of screening.

Our screening test involves a comparison of the educational attainment of self-employed workers with those employed by a corporation or someone else ("salaried" workers) on an occupation by occupation basis. This procedure will overcome the bias built into Wolpin's test from not controlling for occupational mix. In addition, it will allow us to distinguish between occupations with and without customer signalling. The test will also avoid the identification problem between schooling as productivity enhancer and schooling as an indicator of ability. The test is direct, since if a portion of schooling serves to signal a prospective employer, then schooling behavior should differ between those with and without an employer.

Suppose S_1 years of schooling are necessary to acquire the requisite skills for a given occupation. Students intending to work in this occupation for someone else may, however, pursue $S_1 + S_2$ ($S_2>0$) years of schooling, where the additional S_2 years are needed to signal a prospective employer. Students planning to enter business for themselves

will acquire only S_1 years of schooling. Standardized for experience, ability, sex, race, and other demographic characteristics, less educated, self-employed workers should receive on average the same earnings as more educated salaried workers.

The resultant test is not as straightforward as it might appear. While models of educational screening generally predict that workers in the screened sector of an occupational labor market will obtain more education, ceteris paribus, it is not always the case that the self-employed workers will be the unscreened group. Even though self-employed workers do not need to screen themselves, if they are in an occupation which sells labor services directly to the public, they are effectively being employed by their customers. Since customers can rely on the name and reputation of a firm providing a service such as that of an electrician or auto mechanic, the self-employed in these occupations will acquire additional educational credentials (vocational diplomas, trade courses, and the like) to overcome customer uncertainty about their ability.[3]

The key to whether self-employed or salaried workers are the ones screened in a given occupation depends on the relative amount of information those who contract for labor services have on workers' abilities, independent of workers' educational credentials. In almost every occupation those who contract for the labor services of

---

[3]In New Haven, from casual observation we noticed that the local Pontiac dealership displayed no vocational training certificates in their service department, whereas our local mechanic did.

the self-employed will do so on a different basis than those who contract for those of the salaried workers. When an occupation provides services directly to the customer, the customer as contractor will know less about the ability of a self-employed worker than about a firm that hires salaried workers to provide the same services to the customer as part of its business. The firm can rely on internal training programs, job histories, and its personnel files to ensure threshold occupational ability levels regardless of educational credentials, while the customer hiring directly will be forced to make a decision with less information about the self-employed worker. The customer will demand an educational premium of the self-employed worker to overcome the lack of a direct measure of ability, something that the salaried worker will let his firm's reputation cover. In this case, the extra S_2 years of schooling will be acquired by the self-employed worker.

The only case where one would not expect self-employed to have more ecuation than salaried workers is in occupations where the job function is toally internal to the firm and has no direct effect on whether customers purchase the firm's products or not. This would include occupations such as managerial and administrative ones, where the labor service goes into the firm and not into the product. One would expect self-employed managers to have less education than salaried managers, ceteris paribus, because they are not being screened by either their customers or their firms. In other white-collar and in blue-collar occupations, we would expect the reverse.

II. Specification of the Model

With data from the 1970 Census 5% Public Use Sample, we used the following equation to test for screening:

$$S = \beta_0 + \beta_1 \text{Log}(E) + \beta_2 \text{Log}(WW) + \beta_3 \text{Log}(H) + \beta_4 A + \beta_5 SEX + \beta_6 RACE + \beta_7 SOUTH + \beta_8 SMSA + \beta_9 SE(PERM) + \beta_{10} SE(NEW) + \beta_{11} VOCTRAIN + u$$

where

S = years of schooling

Log(E) = logarithm of wage and salary earnings plus self-employment earnings in 1969.[4]

Log(WW) = logarithm of weeks worked in 1969.

Log(H) = logarithm of hours worked per week.[5]

A = age in years.

SEX = dummy variable, with 0 for males.

RACE = dummy variable, with 0 for whites and orientals and 1 for blacks and others.

SOUTH = dummy variable, with 1 for residence in any of the 17 southern states.

SMSA = dummy variable, with 1 for residence outside a Standard Metropolitan Statistical Area (SMSA)

---

[4]The Census defines wage and salary earnings as "wages, salary, commissions, bonuses, or tips" and self-employment earnings as "non-farm business, professional practice, or partnership" earnings. The sum of the two was used since some respondents report both kinds of income.

[5]Hours per week were reported for a sample census week in 1970 and are not mean hours per week.

SE(PERM) = dummy variable, with a value of 1 if the respondent classified himself as self-employed in both 1970 and 1965 and was working in the same occupation in the two years, and a value of 0 otherwise.[6] This is the group of 'permanent" self-employed.

SE(NEW) = dummy variable, with a value of 1 if the respondent classified himself as self-employed in 1970 but either was not self-employed in 1965 or was working in a different occupation, and a value of 0 otherwise. This is the group of "newly" self-employed workers.

VOCTRAIN = dummy variable, with a value of 1 if the respondent reported receiving vocational training and a value of 0 otherwise.[7]

u = random error term.

Our primary interest is in the coefficients of SE(PERM) and SE(NEW), since these will indicate whether there is any difference in educational attainment between self-employed and salaried. The other variables are used mainly to standardize the samples for differences in demographic composition and earnings. SEX and RACE should have positive coefficients because of discriminatory pay practices. SOUTH and SMSA should also have positive coefficents, because of occational differentials in earnings. A(age) should have a negative coefficient, because of the positive impact of experience on earnings. Since productivity is more nearly related to the hourly

---

[6]For those reporting both salary and self-employment earnings, we used the work status they reported to classify them as self-employed or not.

[7]The areas of vocational training listed by the Census are: business and office work; nursing and other health fields; trade and crafts; engineering and science technician and draftsman; agriculture and home economics; and "other fields."

wage rate than annual earnings, Log(WW) and Log(H) have been included in the equation in addition to Log(E).[8] Our hypothesis that employer screening occurs in managerial occupations is then that the coefficients of SE(PERM) and SE(NEW) are negative. The hypothesis that customer screening occurs in professional, sales, craft, operative, unskilled and service occupations is that the coefficients of SE(PERM) and SE(NEW) are positive.

There are two possible sources of bias in the estimate of earnings. The first is that self-employment earnings may be underreported.[9] This will bias upward the coefficients on SE(PERM) and SE(NEW), since it will understate the actual level of earnings for a given level of schooling (and age). The second is that the self-employment earnings reported in the Public Use Sample may include a return to capital

---

[8]The reason is that:

$$\text{Log}(w) \approx \text{Log}\ \frac{E}{H \cdot WW} = \text{Log}(E) - \text{Log}(WW) - \text{Log}\ (H)$$

where w is the hourly wage rate. The approximation sign is used because H is estimated from a sample week.

[9]Computations done by Ono (1972) showed that wage and salary earnings reported in the Public Use Sample equalled 100 percent of National Account totals and non-farm self-employment income in the Public Use Sample was 99 percent of the National Accounts total (Table 4). However, the National Account estimate of self-employment income is based on tax return data, where there is substantial leeway for underreporting.

invested in a small business in addition to labor earnings. This will bias downward the coefficients on SE(PERM) and SE(NEW), because it will overstate the level of self-employed labor earnings for a given level of schooling (and age). To overcome both problems, we estimated a second equation, substituting the logarithm of total personal income (Log(Y)) for Log(E). This may not fully overcome the first bias, since an underreporting of self-employment earnings may be reflected in an underreporting of total personal income. Moreover, the use of total income, which should capture the property income of both salaried and self-employed workers, may not fully overcome the second bias. The reason is that the self-employed may have a greater propensity to invest, since they own their business, or that they may be wealthier to begin with, which may be a dominant reason that they have their own business.

Another bias in the test is caused by the uncertainty students have about whether they will be salaried or self-employed. A reasonable presumption is that any student in doubt about his future employment status will acquire more schooling rather than less to keep both options open. This will bias the coefficients on SE(PERM) and SE(NEW) upward. However, it is for this reason that we split our self-employed group into two samples. The first group, SE(PERM), has the most stable businesses and would presumably have been more certain when young about their future employment status (for example, managing a family business). The second, SE(NEW), are the ones with relatively new businesses, including many who recently switched from salaried positions. This group would probably have been less certain when

young about their future employment status. In occupations without customer screening, we would predict a higher but less significant coefficient on SE(NEW) than on SE(PERM).[10]

The Public Use Sample, unlike the NBER-Thorndyke sample, contains no information on ability. But this should not bias the test, unless the distribution of ability or its covariance with earnings is different among self-employed than among salaried workers. As far as the distribution of ability, there is no a priori reason to suspect a difference between self-employed and salaried workers. As far as the covariance of ability and earnings, we would expect earnings to be directly related to ability for self-employed workers throughout their working career and for salaried workers in their later working years. For salaried workers in their early working years, we would expect earnings to be pegged to schooling in screened occupations. But, by the corollary of the screening hypothesis, ability must vary directly with schooling for the signalling process to remain in equilibrium. Thus, for young salaried workers we would also expect earnings to be positively related to ability.

The vocational training variable VOCTRAIN will allow us an additional test for employer screening. The screening thesis maintains that schooling (after a certain point) serves to signal on-the-job productivity but does not augment it. However, vocational training, by its very definition, is geared to providing job-specific skills.

---

[10] In occupations with customer screening, the uncertain group would behave like the more certain self-employed group and acquire the additional schooling needed for setting up their own business. Therefore, no prediction is offered on the relative magnitudes of the coefficients of SE(PERM) and SE(NEW) in these occupations.

Therefore, on prima facie grounds, we should expect a different relation between schooling and earnings for those with and without vocational training. In particular, we would hypothesize two different sets of relations for white-collar and blue-collar workers.

White-collar (professional and technical, administrative, sales and clerical) workers are generally drawn from a pool of high school graduates and college matriculants (see below). Suppose employers screen the available pool of high school and college students on the basis of schooling level, grades, and other indicators of ability (references, for example) and hire the most able for white-collar positions with the intention of training them (programmers, for example). Those not hired, the less able, may attend a specialized vocational school (a computer programming institute, for example) to acquire specific job-related schools. Employers may then hire from a second pool of prospective candidates, those who graduate from vocational institutes, and select on the basis of demonstrated capabilities. Employers will pay a premium to the first group for their greater (signalled) ability and to the second group for their already acquired job-specific skills. On net, the two groups may have comparable earnings, but the second group will have more years of schooling. In terms of our model, then, we would predict a positive coefficient on VOCTRAIN.

Blue-collar (skilled and craft, semi-skilled and operative, unskilled, and service) workers are generally drawn from a pool of high school drop-outs and graduates (see below). In their case we

might expect self-selection to occur during high school with the less academically capable pursuing vocational training in high school and "dropping out" and the more capable pursuing an academic program and graduating. Employers hiring for blue-collar jobs may then hire from two pools. They may hire high school graduates or near graduates on the basis of their greater demonstrated ability with the intention of training them, and they may also hire high school drop-outs with vocational training on the basis of their acquired skills. Here too the two groups should have comparable earnings--the first because of their greater (signalled) ability and the second for their job-specific skills. But the second group will have less schooling. In terms of our model, then, we would predict a negative coefficient on VOCTRAIN.

III. Results

We extracted full samples of 39 out of the 439 occupations in the 1970 1/100 Census Public Use Sample. The occupations we chose met the following two criteria: (1) the number of self-employed in the occupational sample exceeded 50 and (2) the number of salaried in the sample exceeded 50. Fifty-four occupations fulfilled these two criteria. Of these we selected 39 to be fairly representative of the broad spectrum of skill levels in the occupational hierarchy.[11]

Table 1 shows the mean schooling level for self-employed and salaried as well as the percent self-employed and occupation size for

---

[11] This is not to suggest that these are the only occupations where we suspect screening occurs, only that these are the ones we can most easily test for the occurrence of screening.

Table 1: Mean Education for Salaried and Self-Employed

PUS Code	Occupation	Percent Self-Employed	Mean Education (in years)[a] Salaried	Self-Employed	Occupational Size (1,000s)
A.	Professional & Technical				
001	Accountants	11.1	14.2	14.9	567.9
002	Architects	35.4	16.0	15.7	48.3
031	Lawyers	61.1	17.5	17.5	228.2
062	Dentists	90.7	16.9	17.6	75.0
145	Teachers N.E.C.(except college)[b]	48.4	13.8	13.9	107.0
183	Designers	14.8	13.8	13.8	85.8
185	Musicians and Composers	24.6	13.2	12.6	60.5
191	Photographers	30.8	12.3	12.5	50.0
B.	Managerial and Administrative				
205	Wholesale & Retail Buyers (admin.)	22.0	12.7	11.7	147.5
212	Health Administrators	9.0	14.7	11.5	69.7
216	Building Managers & Superintendents	17.5	11.5	11.8	67.5
231	Retail Sales Managers & Department Heads	6.8	12.4	12.2	181.7
245	Managers & Administrators N.E.C.	37.5	13.0	12.0	2757.5
C.	Sales and Clerical				
265	Insurance Agents, Brokers, & Underwriters	16.8	13.2	13.6	397.6
270	Real Estate Agents & Brokers	35.8	12.9	13.1	206.0
271	Stock & Bonds Salesmen	13.5	14.6	14.5	83.4
284	Retail Salesmen	18.8	11.8	11.5	361.9
305	Bookkeepers	5.0	12.2	12.0	1202.6
321	Estimators & Investigators	5.3	12.9	12.0	213.2
D.	Craft and Skilled				
402	Bakers	13.9	9.6	10.3	85.6
415	Carpenters	18.5	9.8	10.1	646.9
425	Decorators & Window Dressers	20.6	12.0	12.1	52.4
430	Electricians	7.0	11.1	11.4	381.3
453	Jewelers & Watchmakers	41.2	10.6	11.2	28.9
473	Auto Mechanics & Repairmen	14.8	10.2	10.1	640.8
475	Radio & TV Mechanics & Repairmen	25.0	11.5	11.2	104.5
510	Construction & Maintenance Painters	27.9	9.6	9.8	258.9
522	Plumbers & Pipe Fitters	11.3	10.4	10.3	313.6

Table 1 (cont'd)

PUS Code	Occupation	Percent Self-Employed	Mean Education (in years)[a] Salaried	Self-Employed	Occupational Size (1,000s)
E.	Operative & Semi-Skilled				
615	Dressmakers & Seamstresses (except factory)	29.7	9.8	10.2	79.2
631	Meat Cutters & Butchers (except manufacturing)	9.6	10.4	10.1	160.4
680	Welders & Flame-cutters	3.3	10.0	10.0	442.2
714	Cab Drivers & Chauffeurs	14.8	9.9	9.6	122.6
715	Truck Drivers	7.2	9.7	9.7	1075.8
F.	Laborer				
752	Fishermen & Oystermen	52.0	8.9	9.2	17.1
755	Gardeners & Groundskeepers	18.2	8.8	9.0	211.2
G.	Farm				
802	Farm Managers	48.8	11.0	10.8	36.5
H.	Service				
910	Bartenders	24.3	10.5	10.1	138.5
912	Cooks (except private household)	5.8	9.7	10.0	545.4
925	Barbers	60.9	10.3	9.9	140.2
949	Hairdressers & Cosmetologists	38.3	11.3	11.0	381.3

[a]The schooling variable in the Public Use sample is truncated at 6 or more years of college, which was treated as 6 years of college.

[b]N.E.C.: Not Elsewhere Classified.

each of the 39 occupations. The percentage self-employed varies considerably across occupations and ranges from 3 to 91 percent, though half the occupations lie in the 10 to 30 percent interval. (For the labor force as a whole, about 7 percent are self-employed.) No systematic relation is apparent between the percentage self-employed and position on the occupational hierarchy. Schooling levels generally decline down the occupational ladder. For the professional and technical group, mean schooling varies between 12 and 18 years of schooling for both the salaried and self-employed groups; for the managerial and administrative group, the range is 12 to 15 years; and for the sales and clerical group, the range is also 12 to 15 years. In only 2 of the 19 white-collar occupations is the mean schooling level less than 12 years. For the skilled and craft group the range in mean schooling levels is 10 to 12 years; for the operative and semi-skilled group the mean schooling level rounds to 10 years for each occupation; for laborers the mean schooling level is 9 years; for farmers it is 11 years; and for service workers the range is 10 to 11 years. In only 1 out of the 21 blue-collar occupations does the mean schooling level exceed 12 years.

The mean schooling levels of salaried and self-employed workers, unadjusted for differences in earnings and demographic characteristics, follow the hypothesized pattern in some groups but not in others. In the professional and technical group, mean education is higher for self-employed workers in 4 occupations and lower in 2. In the managerial and administrative group, mean schooling is lower for the self-employed

in 4 occupations and higher in only 1. In the sales and clerical group schooling is higher for the self-employed in 2 occupations and lower in 4. In the craft and skilled group, schooling is higher in 6 and lower in 3. In the operative group, it is higher in 1 and lower in 3. In the laborer, farm and service groups it is higher in 3 and lower in 4. The actual schooling levels are fairly close between salaried and self-employed workers. In fact, in 30 of the 39 occupations, schooling levels are within a half a year of each other for the two groups.

Occupational size varies considerably among occupations. The largest occupation in the sample is managers and administrators N. E. C. (not elsewhere classified) with over two-and-a-half million members, and the smallest farm managers with 37,000. About 16 percent of the labor force is represented in this sample and about 22 percent of the self-employed. About 80 percent of the self-employed in our sample fall in the category managers and administrators N. E. C.

Table 2 shows the regression results for selected variables for the two forms of the equation for each of the 39 occupations.[12] The first column shows the coefficient of Log(E) in Form 1 and the fifth column the coefficient of Log(Y) in Form 2. The coefficient of Log(E)

---

[12] Additional forms were tried with interaction terms between the self-employment dummy variable and various demographic characteristics, but the results were largely insignificant. This may have been in part due to the very small subsamples represented by the interaction terms.

Table 2: Regression Results for Selected Variables (S the Dependent Variable)[a]

PUS Code	Occupation	Form 1: S on Log(E) LOG(E)	SE(PERM)	SE(NEW)	VOCTRAIN	Form 2: S on Log(Y) LOG(Y)	SE(PERM)	SE(NEW)	VOCTRAIN
A.	Professional and Technical								
001	Accountants	.528(12.7)	.645(6.2)	.687(5.4)	.601(11.4)	.689(14.9)	.564(5.5)	.601(4.8)	.596(11.4)
002	Architects	.417(3.8)	.243(0.9)	-.735(2.6)	1.025(4.8)	.619(4.3)	.131(0.5)	-.787(2.8)	.994(4.7)
031	Lawyers	.151(4.9)	.175(2.7)	.092(1.2)	.388(5.3)	.208(5.8)	.151(2.3)	.076(1.0)	.382(5.2)
062	Dentists	.169(3.2)	.586(3.3)	.051(0.3)	.006(0.1)	.211(3.4)	.562(3.1)	.027(0.1)	.002(0.0)
145	Teachers N.E.C.(non-college)[b]	.242(2.9)	.342(1.6)	.336(1.4)	.868(4.8)	.442(4.8)	.444(2.0)	.405(1.7)	.860(4.8)
183	Designers	.608(4.8)	.173(0.5)	.298(1.0)	.817(5.0)	.727(5.4)	.099(0.3)	.262(0.9)	.824(5.1)
185	Musicians and Composers	.356(3.2)	-.592(1.6)	.043(0.1)	.536(1.9)	.341(2.7)	-.628(1.7)	.006(0.0)	.519(1.8)
191	Photographers	.042(0.4)	.359(1.4)	.700(2.3)	-.015(0.1)	.359(2.4)	.372(1.5)	.720(2.4)	.051(0.3)
B.	Managerial and Administrative								
205	Wholesale and Retail Buyers	.551(7.2)	-.154(0.7)	-.390(2.1)	-.212(1.5)	.707(7.8)	-.225(1.1)	-.450(2.4)	-.217(1.6)
212	Health Administrators	.952(7.4)	-2.339(4.8)	-2.482(5.2)	.503(2.5)	1.201(8.7)	-2.356(4.9)	-2.526(5.3)	.538(2.7)
216	Building Managers and Superintendents	.530(5.0)	-.220(0.5)	.960(2.3)	-.383(1.5)	.954(7.3)	-.471(1.2)	.692(1.7)	-.345(1.4)
231	Retail Sales Managers and Department Heads	.763(8.5)	-.336(1.0)	.193(0.8)	-.018(0.2)	.867(9.3)	-.372(1.1)	.151(0.6)	-.014(0.1)
245	Managers and Administrators N.E.C.	.545(10.2)	-.883(6.5)	-.343(2.5)	.243(2.2)	.978(14.8)	-.872(6.6)	-.361(2.8)	.241(2.2)
C.	Sales and Clerical								
265	Insurance Agents, Brokers, Underwriters	.541(10.4)	.515(4.4)	.290(2.0)	.660(8.9)	.653(11.7)	.473(4.1)	.245(1.7)	.658(8.9)
270	Real Estate Agents and Brokers	.053(1.3)	.260(2.0)	.218(1.4)	.512(4.8)	.258(4.3)	.207(1.5)	.166(1.1)	.490(4.6)
271	Stock and Bonds Salesmen	.330(3.6)	.048(0.1)	.073(0.2)	.641(3.5)	.574(5.5)	.013(0.0)	-.059(0.2)	.660(3.6)
284	Retail Salesmen	.291(5.9)	--	-.208(2.1)	-.306(3.5)	.465(8.0)	--	-.250(2.5)	-.303(3.5)
305	Bookkeepers	.126(5.4)	.074(0.7)	.205(2.4)	.018(0.6)	.213(8.1)	.055(0.5)	.192(2.2)	.018(0.5)
321	Estimators and Investigators	.495(6.8)	-1.323(4.3)	-.824(2.9)	.451(4.6)	.675(8.2)	-1.392(4.5)	-.811(2.9)	.461(4.7)

Table 2 (cont'd)

PUS Code	Occupation	Form 1: S on Log(E) LOG(E)	SE(PERM)	SE(NEW)	VOCTRAIN	Form 2: S on Log(Y) LOG(Y)	SE(PERM)	SE(NEW)	VOCTRAIN
D.	Craft and Skilled								
402	Bakers	.226(1.8)	.688(2.1)	.964(2.7)	-1.036(5.1)	.315(2.1)	.659(2.0)	.964(2.7)	-1.014(5.0)
415	Carpenters	.190(4.2)	.596(6.1)	.683(6.1)	-1.003(15.1)	.351(6.8)	.597(6.2)	.702(6.3)	-.978(14.8)
425	Decorators & Window Dressers	.269(2.2)	.582(1.9)	.529(1.5)	-.042(0.2)	.589(3.9)	.508(1.7)	.455(1.3)	-.010(0.1)
430	Electricians	.310(5.3)	.722(4.5)	.613(3.2)	-.648(9.7)	.340(5.7)	.709(4.4)	.598(3.1)	-.642(9.6)
453	Jewelers & Watchmakers	.093(0.6)	.679(1.9)	1.623(3.3)	-.446(1.5)	.372(1.7)	.652(1.8)	1.679(3.4)	-.459(1.5)
473	Auto Mechanics & Repairmen	.348(7.3)	.256(2.4)	.185(1.7)	-.915(16.4)	.433(8.8)	.250(2.4)	.179(1.6)	-.903(16.2)
485	Radio & TV Mechanics & Repairmen	.205(2.4)	.174(0.9)	.240(1.1)	-.589(4.6)	.285(3.0)	.172(0.9)	.229(1.0)	-.570(4.5)
510	Construction & Maintenance Painters	.302(4.0)	.549(4.0)	.582(3.6)	-.853(7.4)	.320(3.9)	.537(3.9)	.575(3.6)	-.849(7.4)
522	Plumbers & Pipe Fitters	.480(7.1)	.516(3.4)	-.059(0.3)	-.806(10.2)	.481(7.0)	.493(3.2)	-.089(0.5)	-.806(10.2)
E.	Operative and Semi-Skilled								
613	Dressmakers & Seamstresses (except factory)	.141(1.5)	.701(2.8)	.585(2.1)	-1.144(5.3)	.176(1.2)	.682(2.7)	.563(2.0)	-1.129(5.3)
631	Meat Cutters & Butchers (except manufacturing)	.428(5.0)	-.174(0.7)	-.001(0.0)	-.706(5.9)	.564(5.3)	-.185(0.8)	-.050(0.2)	-.700(5.9)
680	Welders & Flame-Cutters	.374(6.2)	.543(2.1)	.750(2.7)	-.804(11.4)	.434(6.6)	.497(2.0)	.705(2.5)	-.797(11.3)
714	Cab Drivers & Chauffeurs	.096(0.3)	.106(0.4)	.029(0.1)	-.820(4.7)	.096(1.0)	.106(0.4)	.029(0.9)	-.814(4.7)
715	Truck Drivers	.370(10.4)	.334(2.9)	.051(0.4)	-.929(16.0)	.447(11.7)	.301(2.6)	.028(0.3)	-.923(15.9)
F.	Laborer								
752	Fishermen & Oystermen	-.090(0.5)	-.145(0.3)	1.666(3.0)	-2.304(3.5)	.219(0.8)	-.119(0.2)	1.689(3.0)	-2.297(3.5)
755	Gardeners & Groundskeepers	.266(3.4)	.568(2.7)	.122(0.5)	-1.472(8.6)	.424(4.5)	.546(2.6)	.074(0.3)	-1.1441(8.4)
G.	Farm								
802	Farm Managers	.123(1.7)	--	.002(0.0)	-.758(2.0)	.930(6.3)	--	-.078(0.3)	-.710(2.0)
H.	Service								
910	Bartenders	.303(3.7)	-.085(0.4)	-.224(1.1)	-.798(4.9)	.322(3.4)	-.106(0.5)	-.247(1.2)	-.775(4.8)
912	Cooks (ex. priv. household)	.126(2.7)	.146(0.7)	.517(2.6)	-1.330(14.0)	.137(2.8)	.136(0.7)	.512(2.6)	-1.324(14.0)
925	Barbers	.181(2.4)	-.145(1.0)	-.099(0.5)	-.866(5.9)	.246(2.6)	-.151(1.1)	-.101(0.5)	-.846(5.7)
999	Hairdressers & Cosmetologists	.059(1.8)	.002(0.0)	.115(1.4)	-.292(3.9)	.061(1.7)	.001(0.0)	.115(1.4)	-.292(3.9)

[a] t-statistics are shown in parantheses.

[b] N.E.C.: Not Elsewhere Classified.

is significant in all occupations except nine. The coefficients are generally highest in professional and managerial occupations, lower for sales and clerical workers, and lowest for blue-collar workers. This indicates that the returns to schooling are greater for white-collar workers than for blue-collar ones. (See Eckaus (1973), Wolff (1977) and Wolff and Bushe (1976) for similar results.) The coefficient of Log(Y) is significant in all occupations except five. The coefficient value of Log(Y) and its significance level is greater than those of Log(E) in 34 out of the 39 occupations, but the coefficient values of Log(Y) and Log(E) are highly correlated.

The signs of the coefficients of SE(PERM) and SE(NEW) conform very closely to prediction. In the professional and technical group, 14 out of the 16 coefficients are positive in Forms 1 and 2. In the managerial group, the coefficients are negative in 8 out of 10 cases in the two Forms. In the sales and clerical group, the coefficients are positive in 8 out of 11 cases for Form 1 and 7 out of 11 cases for Form 2. In the craft and skilled group, the signs are positive in 17 out of 18 cases, and in the operative and semi-skilled group in 8 out of 10 cases. In the laborer and service groups, the coefficient signs are mixed, with 5 negative and 7 positive.

The coefficient values and their significance level vary considerably among occupations, though the two are highly correlated. Self-employed accountants acquired, on average, over half a year more schooling than salaried accountants, as did the permanently self-employed dentists and the newly self-employed photographers compared to their salaried counterparts. Self-employed health administrators

averaged more than two years less schooling than salaried health administrators, and self-employed managers N.E.C. about a year less schooling than salaried managers. Permanently self-employed insurance agents, brokers, and underwriters spent, on average, a half year more in school than their salaried counterparts, while self-employed estimators and investigators spent about a year less in school. Self-employed bakers, carpenters, decorators and window dressers, electricians, jewelers and watchmakers, construction and maintenance painters, dress-makers and seamstresses, and welders and flame-cutters acquired between a half and about one-and-a-half more years of schooling than their salaried counterparts. The coefficents are significant at the 5 percent level and have the predicted sign in about 30 percent of the cases in the professional and technical group, 50 percent of the cases in the managerial group, 40 percent of the cases in the sales and clerical group, 60 percent of the cases in the craft group, and 50 percent of the cases in the operative group.

In the managerial and administrative group, the coefficient of SE(NEW) was predicted to be higher than that of SE(PERM). This is the case in only 3 out of the 5 occupations. The coefficents of SE(PERM) and SE(NEW) in Form 1 have the same sign as the coefficients of SE(PERM) and SE(NEW) in Form 2 in all cases except one. The coefficients of SE(PERM) and SE(NEW) are less in Form 2 than in Form 1 in 83 percent of the cases. This suggests an upward bias on the coefficents in the labor earnings Form. However, the coefficient values are quite close in the two Forms, indicating that the bias is small.

The VOCTRAIN variable also behaves closely to prediction. Among white-collar workers the coefficient of VOCTRAIN is positive in 74 percent of the cases, and of the positive coefficients significant at the 5 percent level in 79 percent of the cases. Among blue-collar workers the coefficient of VOCTRAIN is negative in 100 percent of the cases and of these significant at the 1 percent level in 86 percent of the cases. Among the white-collar workers, 47 percent of the coefficient are above .5, indicating that vocational training increased the average stay in school by at least half a year for this group. Among the blue-collar workers, 86 percent of the coefficients are less than -.5 and 29 percent less than -1, indicating an appreciable shortening of schooling with vocational training.

IV Conclusion

The screening hypothesis states that certain classes of workers obtain more schooling than that necessary for the specific or general skills required in their work in order to signal employers or customers who may contract their services. Among those working for someone else, extra schooling will be acquired to signal a prospective employer. Among self-employed managers, no additional schooling will be obtained, since their services are administrative and not contracted by anyone else. Among other self-employed workers, extra schooling will be pursued to attract prospective clients. Their schooling will exceed that of salaried workers in the same occupation in order to compete successfully against the firms in which the latter are employed.

The empirical results provide broad support for the screening

hypothesis. In the managerial and administrative group, the evidence strongly supports the case for employer screening. This is particularly true for the category managers N.E.C., who comprise 22 percent of the sample labor force and 80 percent of the self-employed workers in the sample. The actual magnitude of the screening portion of ecuation is relatively modest--between a half and a full year of schooling out of 12 to 15 years. In the professional and technical, sales and clerical, craft and skilled, and operative and semi-skilled groups, the results indicate a pervasive pattern of customer screening. Here too the relative magnitude of the screening portion of schooling is modest. Among skilled and semi-skilled workers, where we might expect minimal employer screening, between a half and a full year of schooling out of 10 to 12 years constitutes the signalling portion.

Additional corroboration of the screening hypothesis is provided by the results for the vocational training variable. In the case of blue-collar workers, we hypothesized that some self-selection occurs during the high school years. The more (academically) able complete high school, while the less able acquire vocational training and "drop out." In the case of white-collar workers, we hypothesized that the more able are hired directly by an employer from high school or college, while the less able continue their schooling in some vocational program. In both cases, the acquisition of specific job-related skills serves as a substitute for the greater ability signalled by formal schooling. An employer pays those with vocational training a premium for their acquired skills and those with formal schooling a premium for their greater ability. This hypothesis was also confirmed by our empirical results.

References

James Albrecht, "The Use of Educational Information by Employers," Econometric Society Meeting, Winter 1974.

Kenneth Arrow, "Higher Education as a Filter," Journal of Public Economics, July 1973, Vol. 2, No. 3, pp. 193-216.

Richard Eckaus, "Estimation of the Return to Education with Hourly Standardized Incomes," Quarterly Journal of Economics," February 1973, Vol. 87, No. 1, pp. 121-131.

_____, Estimating the Returns to Education: A Disaggregated Approach, Technical Report, Carnegie Commission on Higher Education, 1973

Richard Layard and George Psacharopoulos, "The Screening Hypothesis and the Return to Education," Journal of Politial Economy, Sept.-Oct. 1974, Vol. 82, No. 5, pp. 985-998.

Edward Lazear, "Academic Achievement and Job Performance: Note,"" American Economic Review, March 1977, Vol. 67, No. 2, pp. 252-254.

Mitsuo Ono, "Preliminary Evaluation of 1969 Money Income Data Collected in the 1970 Census," Proceedings of the American Statistical Association, 1972.

John Riley, "Towards a Test of the Educational Screening Hypothesis," mimeo.

Michael Spence, "Job Market Signalling," Quarterly Journal of Economics, Aug. 1973, Vol. 87, No. 3, pp. 355-374.

Joseph Stiglitz, "The Theory of 'Screening', Education, and the Distribution of Income," American Economic Review, June 1975, Vol. 65, No. 3, pp. 283-300.

Paul Taubman and Terrence Wales, "Higher Education, Mental Ability and Screening," Journal of Political Economy, Jan.-Feb. 1973, Vol. 81, No. 1, pp. 28-55.

David Wise, "Academic Achievement and Job Performance," American Economic Review, June 1975, Vol. 65, No. 3, pp. 350-366.

Edward Wolff, "Schooling and Occupational EArnings," Review of Income and Wealth, 1977 (forthcoming).

Edward Wolff and Dennis Bushe, "Age, Education, and Occupational Earnings Inequality," NBER Working Paper No. 149, Sept. 1976.

Kenneth Wolpin, "Education and Screening," NBER Working Paper No. 102, Aug. 1975.