Human Capital and Skill Specificity

by

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Abstract

Two recent papers, Neal (1995) and Parent (2000) have presented evidence in favour of the importance of industry specific human capital. The authors argued that some or all of the previous evidence on firm specific capital may in fact have been spurious, due to a correlation between firm and industry specific capital. The evidence in Neal (1995) is an indirect method of detecting industry specific capital using the Displaced Worker Surveys. It is indirect because there is no measure of industry tenure. The method is based on a comparison of wage changes for industry switchers compared with industry stayers after displacement. In this paper we argue that rather than being specific to industry, human capital is specific to a small number of basic skills. Using the same methodology and data sources as Neal (1995) we find that when skill status is taken into account there is little evidence of industry specific human capital. The evidence instead is more consistent with basic skill specific human capital.

1 Introduction

Human capital theory has been the basis of a huge literature studying the determination of earnings since the seminal work of Becker (1964), Ben Porath (1967), Mincer (1974) and many others.[1] There is by now quite general agreement that human capital plays a major role in the determination of earnings. One aspect of human capital that was emphasized at a very early stage was the importance of assessing the degree of specificity. Becker (1964) focussed on the dichotomy between firm specific and general capital, and this stimulated a great deal of work on the implications of specific capital for turnover and various incentive problems in financing firm specific capital.[2] This initial focus on firm specific capital also led to attempts to measure the relative importance of specific capital by examining the effects of firm tenure on earnings profiles. This literature produced conflicting evidence on the magnitude of tenure effects.[3] More recently, the whole issue of the source of the specificity has been examined. In particular it has been argued that the tenure effect may be capturing industry specific capital rather than firm specific capital.

Two recent papers, Neal (1995) and Parent (2000), provide evidence to suggest that industry specificity is much more important than firm specificity. Neal (1995) follows an indirect approach to assessing industry specificity using the U.S. Displaced Worker Surveys. Parent (2000) follows a direct approach using U.S. panel data. In this paper we examine the hypothesis that, for the most part, human capital is neither firm nor industry specific, but instead can be represented by a small number of skills that are largely general across firms and industries. We

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[1] See Willis (1986) for a survey.

[2] See Parsons (1986), section 4, and the references therein.

[3] See, for example, Abraham and Farber (1987); Altonji and Shakotko (1987); Topel (1991); Altonji and Williams (1992); Abowd, Kramarz, and Margolis (1999).

re-examine the Neal evidence on industry specificity, and using the same methodology and data set, we show that the evidence for industry specificity is weak, and that instead the data are largely consistent with a more general skill concept of human capital.

2 Human Capital and General Skill Measures

The most basic measures of general human capital usually studied in the human capital earnings function literature are years of education and years of labour market experience. Analyses of firm or industry specific human capital then typically add tenure with a firm and years of experience in the current industry to capture these types of human capital. This is the approach directly taken in Parent (2000), and indirectly in Neal (1995). In our approach to a broad skill based measure of human capital we build on the research of Ingram and Neumann (1999). These authors argue that education per se does not provide an adequate measure of skill and propose instead a measure based on observed skill characteristics of the job. In their paper, Ingram and Neumann use their skill measure to reinterpret the time series data on the return to education. In particular they allow for heterogeneity by skill within education groups and obtain the very interesting result that return to education purged of these other skill effects has been constant since 1970.

The Ingram/Neumann measure of skill uses information in the Census Population Survey (CPS) and the Dictionary of Occupational Titles (DOT) on characteristics such as verbal and mathematical ability, motor skills and strength requirements to attach to each worker in the CPS the skill level required to perform the job that he or she occupies. The DOT actually provides information on 53 characteristics. Ingram and Neumann (1999) use factor analysis to combine similar characteristics into broader skill characteristics. [4]

For the purposes of our analysis we use simplified versions of the Ingram/Neumann measure. In particular we begin by characterising a worker's skill as equivalent to the main skill

[4]See Ingram and Neumann (1999) for more a detailed discussion.

used in the occupation defined at the 3 digit level. In the literature on industry specific capital, the capital is "lost" when the individual changes industry in the sense that it is not being used (or, perhaps more importantly, paid for) in the new industry. It need not be lost altogether (except for depreciation which may apply to all capital, and which may vary with use) in the sense that the capital would still be there (subject again to some depreciation) and could be used following a return to the original industry. Similarly, when an individual undergoes a job change that also changes the main skill used, that skill is not lost altogether but it is no longer paid for. In the extreme, if the skill measure that we use is a true measure of any specificity in human capital then, then an exogenous change in industry that is not accompanied by a change in the main skill used will have no effect on wages.

3 Evidence of Specificity from the Displaced Worker Surveys

The Displaced Worker Surveys (DWS) for the years 1984, 1986, 1988 and 1990 are the data sources used in Neal (1995). Neal's argument in favour of the importance of industry specific human capital is based primarily on the observation that the profile of wages after displacement with respect to *pre*-displacement firm tenure for workers who do not change industry is similar to the wage tenure profile observed in a cross section of workers. The conclusion is thus: "a complete explanation for the observed relationship between wages and seniority must involve factors that are not truly firm-specific but rather specific to an industry or particular line of work. Existing models of matching, firm specific investments, and backloaded compensation schemes (that prevent shirking) provide no rationale for a strong correlation between wages on a given job and tenure on a previous job." [5]

Neal's (1995) analysis of industry specific capital is an indirect one. A direct approach would correspond to estimating Neal's equations (1)-(3):

$$w_1 = \alpha \text{ experience} + \theta \text{ industry tenure} + \gamma \text{ firm tenure} + X\beta + \epsilon_1 \qquad (1)$$

[5] Neal (1995), p. 654.

$$w_2 = \alpha \text{ experience} + \theta \text{ industry tenure} + X\beta + \epsilon_2 \quad (2)$$

$$w_3 = \alpha \text{ experience} + X\beta + \epsilon_3 \quad (3)$$

where w_1 is the wage on the predisplacement job, w_2 is the new wage for workers whose industry does not change after displacement (stayers), w_3 is the wage for workers who do change industry (switchers), and X is a vector of unchanging worker characteristics such as education. In Neal's analysis, the mean zero, independent, error terms capture match specific effects on productivity. If workers were moved from and to jobs exogenously, and the relevant data were available, estimates of the parameters of equations (1) - (3) would provide the required evidence on human capital specificity.

For stayers the wage loss after displacement is less than the wage loss for switchers by:

$$\theta \text{ industry tenure}$$

for workers with the same X characteristics and the same firm tenure prior to displacement. Thus, if industry specific human capital is important the wage loss for switchers will be more than for stayers and the amount will be proportional to industry tenure. Neal does not test this hypothesis directly because of possible problems of endogenous job changes and the absence of data on industry tenure in the DWS. Instead, he estimates the following equation separately for switchers and stayers:

$$\Delta \ln w = \beta_0 + \beta_1 \text{ experience} + \beta_2 \text{ experience}^2 + \beta_3 \text{ tenure} + \beta_4 \text{ tenure}^2 + Z\zeta + \epsilon \quad (4)$$

where the experience and tenure variables both refer to pre-displacement values, and the Z are a set of controls.[6] Neal argues that since the model (1) - (3) implies that the wage cost of switching industry should vary positively with pre-displacement industry tenure, in "the absence of direct

[6] See Neal (1995), pp. 656-57, for more details.

controls for industry tenure, we expect to observe positive correlations between the wage cost of switching industries and pre-displacement measures of both experience and firm tenure." (Neal, 1995: p. 657.)

Neal thus establishes evidence for the importance of industry specificity by showing that switchers with more pre-displacement experience or tenure will suffer a larger wage loss than switchers with less, and that this relative loss (by experience or tenure) will be smaller for stayers. In his specific example for males, one worker is displaced after working 10 years for the same employer; the other is displaced during the first year of his career. If both workers switched industry, the more experienced worker's losses are 27% greater than the less experienced. If neither worker switched industry, the more experienced worker's losses are only 13% greater than those of the less experienced.[7]

In our first test of the relative importance of industry specific capital and basic skill specific capital we re-estimated Neal's equation (4), subdividing his sample of industry switchers into those who also switched basic skill and those who did not. If industry is the important source of specificity then the subdivided sample should yield similar results for the skill switchers and stayers in the sense that both should show larger relative losses than the industry stayers. If industry is relatively unimportant and basic skill specificity matters, the industry switchers who also switched skill should have greater relative losses for the more experienced workers than the industry switchers who did not switch skills. The data set was constructed to exactly replicate

[7] Neal categorizes the results for females as "not so dramatic". In fact, the point estimates yield relative losses for the more experienced worker of 19% for the switchers and 7% for the stayers which shows a very similar percentage point gap between switchers and stayers to that for the males. Neal's concern is with the statistically insignificant coefficients on the experience variables for females which he conjectures may be a noisier measure for females and hence less correlated with industry tenure. It may also be due to a different relationship between experience and tenure for females than for males. These two variables are generally positively, and often highly correlated, so that estimates of the partial effect of experience, holding tenure constant may be very sensitive to the particular reasons for the "independent" variation.

Neal's data set.[8]

The results comparing industry switchers with industry stayers are as reported in Neal. However, the estimates from the sub-samples within industry switchers are not what would be expected if industry specificity was the dominant feature, but instead show a pattern that favours the relative importance of basic skill specificity. Following Neal's method of comparing the relative wage losses for the more and less experienced workers, within industry switchers the skill switchers have a much larger loss than the skill stayers. The results are given in the top half of Table 1.[9] In the last column we replicate the experiment reported in Neal (1995) that compares a worker who is displaced after 10 years with the same firm (experience = 10, tenure = 10) with a worker who is displaced in the first year of employment (experience = 0, tenure = 0). In the data the average displaced worker has about 15 years of experience and 5 years of tenure. This leads us to prefer a comparison of an inexperienced worker with the more typical hypothetical worker presented in the first column. An intermediate case is presented in the middle column.

The results are quite striking. Comparing industry switchers and stayers, the relative losses for the more experienced worker are at least twice as large for the switchers as for the stayers. In the first column, for example, the loss for the industry switchers is -.2369 compared to -.1237 for the industry stayers. This is Neal's basic result. However, the large relative loss for the industry switchers is largely due to the larger losses of the industry switchers who also switch skill. This is especially so for the more representative comparisons in the first and second column. In the first column, for example, the loss is doubled (-.3306 vs. -.1647) if there is a skill switch. Similarly, the low relative loss for the average industry stayer is almost entirely due to the small losses of the industry stayers who are also skill stayers. Indeed, the industry stayers

[8] We are grateful to Derek Neal who provided us with his original code to make this possible.

[9] The sample is the same as Neal (1995) except for the exclusion of 2.8% of the observations which were top-coded. The results are almost identical if these observations are included.

who switch skill have the same losses as the average industry switcher (-.2651 vs. -.2369).

To pursue these differences further, the sample was re-divided into basic skill switchers and stayers and this time the basic skill switchers are subdivided into industry switchers and industry stayers. The estimates are given in the bottom half of Table 1. The magnitude of the difference between skill switchers and skill stayers is substantially larger than the difference between industry switchers and stayers in the more representative first and second columns. In the first column, for example, the loss for the skill switcher is -.3070, while the loss for the skill stayer is -.1209. Whereas the industry stayer who switched skill had the same losses as the average industry switcher, the skill stayer who switched industry suffers a much smaller loss than the average skill switcher. In the first and second columns the losses of the average skill switcher are about double those of the skill stayer than switches industry. The evidence in Table 1 shows a consistent ranking of losses - skill switchers losses are largest, irrespective of whether they switch industry, and skill stayers are the smallest, irrespective of whether they switch industry. These conclusions continue to hold if the data set is updated to 2000. The results are reported in Table 2. They show very similar estimates with the same pattern and relative loss rankings as Table 1.

The coefficient estimates from which the results in Tables 1 & 2 were derived are reported in Tables 3 & 4. These show an interesting difference in the results for the simple comparison of switchers and stayers of basic skill compared to industry. The larger losses for the switcher who is more experienced shows up in the individual coefficients for both firm tenure and general experience for the industry switcher, but only through general experience for the skill switcher. To the extent that basic skills survive across firm switches more frequently than industry, and that firm tenure and experience are themselves correlated, this result is not surprising. In fact, there arise some general difficulties in interpreting the differences in the firm tenure and general experience coefficients separately. Workers of the same experience with shorter firm tenure may be more mobile or less stable workers that differ in other ways. In addition, in the indirect approach, firm tenure and experience are both imperfect but correlated proxies for unobserved industry tenure. Neal's experiment considers the joint movement in firm tenure and general experience where the more "experienced" worker has more of both. Our analysis uses the same experiment.

Neal subjected his basic OLS results to various robustness checks including modelling the selection into industry switcher or stayer status. Using the same selection model for industry switching, we re-estimated the wage equations as in Neal (1995) with the further subdivision into skill switcher or skill stayer. We used Neal's selection model for industry, but did not specify any selection process for occupation switches.[10] The results are presented in Table 5. The results are broadly similar to those in Table 1. Again the large relative losses for the average industry switcher come primarily from the worker who also switches skill, and the small relative losses for the industry stayers again come largely from those who also stay in the same skill. The relative loss rankings are also broadly similar, although the typically larger relative losses for the skill switchers are less exaggerated. The coefficient estimates on which the results in Table 5 are based are presented in Table 6. They are similar to the OLS estimates in Table 3. Overall, our analysis using Neal's basic indirect methods suggests that the evidence advanced by Neal (1995) to support the hypothesis of important industry specificity is more supportive of skill specificity with industry specificity playing a more minor role.

Neal's paper concluded with a final piece of evidence of the importance of industry specificity by showing that for both industry stayers and switchers, post-displacement wages are positively correlated with pre-displacement tenure but that this link is stronger among displaced workers who stay in their pre-displacement industry. This result is replicated in Parent (2000) using the NLSY and the PSID. As occurs with Neal's main source of evidence, incorporating the

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[10]Neal's selection model uses primarily the level and growth rate of the pre-displacement industry as selection variables, though in this section of the paper (Table 3) pre-displacement industry employment growth is also added to the wage equation. Our re-analysis was conducted under the null hypothesis that industry specificity was important and skill was not. The group of industry switchers who also switch skill are then a random sample of all industry switchers. Neal's selection model is then applied to a data set consisting of all the industry stayers in the DWS sample and a random sample of the industry switchers in the DWS sample.

basic skill measure into the alternative approach changes the picture. Again, the evidence for industry specificity is weakened, though this approach provides a less clear picture of the relative roles of industry and skill.

Table 7 presents our re-examination of this form of evidence using our basic skill measure. The first column presents a standard log wage regression using the pre-displacement wage as the dependent variable to establish a benchmark. This regression shows significant returns to both firm tenure and experience. The remaining columns use the post-displacement wage as the dependent variable but splits the sample into industry switchers and industry stayers. Neal argues that if you stay in the industry you were displaced from you should receive a return from your industry specific capital. Since there is no direct measure of this in the regression the effect will be picked up by pre-displacement job tenure and experience. Those that switch industry will not have this effect so the coefficients on pre-displacement tenure and experience for the industry stayers will be higher. The second and fifth columns show that this is in fact the case. Both pre-displacement experience and job tenure have larger effects for the industry stayers.

However, subdividing the industry stayers into skill switchers and stayers casts some doubt on this evidence of industry specific effects. In particular, the large effect of tenure for the industry stayer is due mainly to the sub-group who are also skill stayers. Similarly, the small effect of experience for industry switchers is largely due to the subgroup who also switch skill. The overall effects are given in Table 8. The pattern of results is the same at the three points of evaluation. For the most representative group (first column), the estimates clearly show the larger effect for the industry stayer (.3878 vs. .2088). However, the breakdown by skill indicates that the large effect for the industry stayer is primarily from the sub-group of skill stayers (.3959 vs. .2905). Similarly, the small effect for industry switchers is primarily due to the sub-group of skill switchers (.1358 vs. .2226).

Neal emphasizes the importance of the large effect of pre-displacement tenure on post-displacement wages for industry stayers, noting that it is almost as large as the current firm tenure return in the cross section regression in Table 7, column 1. He notes that this is difficult to reconcile with models of firm specific investment. However, since the effect is primarily through the sub-group of skill stayers, it is not clear that this should be taken as convincing evidence of industry specific capital even if it casts doubt on substantial firm specific capital. Given that the sub-divided analysis was carried out under the null hypothesis of no importance for skill change status given industry status, (i.e. no model was specified for skill status changes) and the imprecision of some of the estimates, it is difficult to assess the relative role of skill and industry. However, it again appears clear that industry effects are probably picking up at least some, if not primarily, skill effects.

4 Some Conclusions and Future Work

It is important to establish the degree of specificity of human capital from a policy point of view. There is considerable evidence to suggest that in the new economy there is more movement of workers across firms, industries and occupations. The less specific the human capital in a given labour force, the more easily the labour force can adapt to the increased movement. An interesting question is whether human capital is substantially firm, industry or occupation specific, or whether it can be represented by a small number of basic skills that can be used equally well in a wide variety of situations. To the extent that a country's human capital is more basic skill specific, it may adjust more easily to technical change requiring worker mobility.

Overall, our analysis of the basic skill measure, using the same basic methodology as Neal (1995), is consistent with basic skill as the major source of specificity with industry specific capital possibly being quite small. In future work we will replicate this indirect analysis using comparable Canadian data from the 1986 Canadian Displaced Worker Survey.

Evidence on industry specificity, and against firm specificity, has also been produced using a direct approach with U.S. panel data (NLSY and PSID) in Parent (2000). Kambourov and Manovskii (2002) have extended the analysis using the PSID to incorporate occupation specificity. In future work we will also examine both U.S. and Canadian panel data using the more direct approach to identifying industry specificity by Parent (2000) that is closely related to Neal's equations (1) - (3). The results of Kambourov and Manovskii (2002) suggest that the results obtained here indicating a possibly negligible role for industry specificity may also hold in the direct approach when some measure of skill is introduced.

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Table 1

Relative Losses for More Experienced Workers After Displacement:

Neal Sample 1984-1990, United States Males

By Industry Status

	E=15; T=5	E=10; T=5	E=10; T=10
INDUSTRY SWITCHER	-.2369 (.0341)	-.1975 (.0282)	-.2639 (.0340)
Industry & Skill Switcher	-.3306 (.0504)	-.2597 (.0414)	-.3035 (.0504)
Industry Switcher & Skill Stayer	-.1647 (.0472)	-.1497 (.0391)	-.2332 (.0466)
INDUSTRY STAYER	-.1237 (.0400)	-.1050 (.0326)	-.1419 (.0389)
Industry & Skill Stayer	-.0831 (.0457)	-.0724 (.0370)	-.1070 (.0440)
Industry Stayer & Skill Switcher	-.2651 (.0906)	-.2198 (.0751)	-.2709 (.0914)

By Skill Status

SKILL SWITCHER	-.3070 (.0437)	-.2440 (.0360)	-.2901 (.0439)
Skill & Industry Switcher	-.3306 (.0504)	-.2597 (.0414)	-.3035 (.0504)
Skill Switcher & Industry Stayer	-.2651 (.0906)	-.2198 (.0751)	-.2709 (0914)
SKILL STAYER	-.1209 (.0328)	-.1086 (.0269)	-.1681 (.0321)
Skill & Industry Stayer	-.0831 (.0457)	-.0724 (.0370)	-.1070 (.0440)
Skill Stayer & Industry Switcher	-.1647 (.0472)	-.1497 (.0391)	-.2332 (.0466)

Note: E is experience in years; T is firm tenure in years; standard errors in parentheses

Table 2

Relative Losses for More Experienced Workers After Displacement
Full Sample 1984-2000, United States Males

By Industry Status

	E=15; T=5	E=10; T=5	E=10; T=10
INDUSTRY SWITCHER	-.2282 (.0285)	-.1848 (.0234)	-.2388 (.0282)
Industry & Skill Switcher	-.2977 (.0440)	-.2358 (.0363)	-.2814 (.0439)
Industry Switcher & Skill Stayer	-.1815 (.0376)	-.1513 (.0309)	-.2130 (.0368)
INDUSTRY STAYER	-.1424 (.0339)	-.1206 (.0275)	-.1604 (.0325)
Industry & Skill Stayer	-.1221 (.0390)	-.1027 (.0315)	-.1347 (.0369)
Industry Stayer & Skill Switcher	-.2348 (.0734)	-.2035 (.0604)	-.2788 (.0733)

By Skill Status

SKILL SWITCHER	-.2725 (.0377)	-.2190 (.0311)	-.2707 (.0378)
Skill & Industry Switcher	-.2977 (.0440)	-.2358 (.0363)	-.2814 (.0475)
Skill Switcher & Industry Stayer	-.2348 (.0734)	-.2035 (.0604)	-.2788 (0733)
SKILL STAYER	-.1520 (.0270)	-.1272 (.0219)	-.1746 (.0260)
Skill & Industry Stayer	-.1221 (.0390)	-.1027 (.0315)	-.1347 (.0369)
Skill Stayer & Industry Switcher	-.1815 (.0376)	-.1513 (.0309)	-.2130 (.0368)

Note: E is experience in years; T is firm tenure in years; standard errors in parentheses.

Table 3

Determinants of Changes in Log Wages for Displaced Male Workers, 1984-1990

	Industry Switcher			Industry Stayer			Skill Switcher	Skill Stayer
	All	Skill Sw	Skill St	All	Skill Sw	Skill St		
Experience	-0.0143	-.0246	-.0060	-.0086	-.0250	-.0045	-.0234	-.0049
	(.0038)	(.0057)	(.0053)	(.0042)	(.0097)	(.0048)	(.0049)	(.0036)
$Exper^2$ *100	0.0259	.0419	.0120	.0196	.0637	.0096	.0432	.0096
	(.0107)	(.0160)	(.0147)	(.0110)	(.0268)	(.0123)	(.0137)	(.0095)
Tenure	-0.0174	-.0122	-.0222	-.0077	-.0050	-.0076	-.0114	-.0149
	(.0046)	(.0069)	(.0061)	(.0051)	(.0129)	(.0057)	(.0060)	(.0042)
$Tenure^2$ *100	0.0275	.0228	.0364	.0022	-.0346	.0044	.0143	.0202
	(.0167)	(.0252)	(.0225)	(.0189)	(.0527)	(.0204)	(.0223)	(.0154)
Schooling	-.0053	-.0025	-.0094	.0062	.0187	.0014	.0007	-.0060
	(.0049)	(.0083)	(.0060)	(.0055)	(.0122)	(.0062)	(.0069)	(.0043)
White	-.0534	-.0527	-.0579	-.0398	.0658	-.0893	-.0177	-.0619
	(.0374)	(.0581)	(.0486)	(.0473)	(.0955)	(.0561)	(.0492)	(.0364)
Married	.0482	.0298	.0684	.0211	.0015	.0147	.0236	.0454
	(.0249)	(.0381)	(.0330)	(.0293)	(.0648)	(.0338)	(.0324)	(.0237)
Years since displacement	.0064	-.0131	.0239	.0154	-.0068	.0212	-.0110	.0204
	(.0096)	(.0145)	(.0129)	(.0107)	(.0253)	(.0120)	(.0125)	(.0089)
Weeks Unemployed	-.0044	-.0039	-.0048	-.0023	-.0012	-.0025	-.0035	-.0043
	(.0005)	(.0007)	(.0007)	(.0007)	(.0013)	(.0008)	(.0006)	(.0005)
R^2	.17	.20	.18	.08	.18	.08	.18	.13
N	1653	768	885	910	224	686	992	1571

Notes: The specification is as in Neal (1995); it includes year of displacement dummies and controls for changes in occupational affiliation. Standard errors are given in parentheses.

Table 4

Determinants of Changes in Log Wages for Displaced Male Workers, 1984-2000

	Industry Switcher			Industry Stayer			Skill Switcher	Skill Stayer
	All	Skill Sw	Skill St	All	Skill Sw	Skill St		
Experience	-0.0147	-.0227	-.0090	-.0091	-.0180	-.0075	-.0203	-.0080
	(.0031)	(.0049)	(.0040)	(.0036)	(.0078)	(.0041)	(.0042)	(.0029)
$Exper^2$ *100	0.0242	.0413	.0118	.0191	.0471	.0146	.0382	.0124
	(.0083)	(.0135)	(.0105)	(.0090)	(.0215)	(.0101)	(.0115)	(.0073)
Tenure	-0.0131	-.0104	-.0159	-.0105	-.0136	-.0094	-.0112	-.0130
	(.0037)	(.0059)	(.0048)	(.0041)	(.0096)	(.0046)	(.0050)	(.0033)
$Tenure^2$ *100	0.0153	.0087	.0236	.0172	-.0099	.0199	.0058	.0236
	(.0138)	(.0218)	(.0177)	(.0150)	(.0373)	(.0166)	(.0188)	(.0122)
Schooling	-.0063	-.0009	-.0115	.0062	.0079	.0062	-.0010	-.0049
	(.0040)	(.0070)	(.0048)	(.0043)	(.0099)	(.0049)	(.0058)	(.0034)
White	-.0530	-.0428	-.0576	-.0123	.0711	-.0513	-.0099	-.0476
	(.0286)	(.0451)	(.0367)	(.0348)	(.0681)	(.0416)	(.0377)	(.0273)
Married	.0310	.0166	.0402	.0141	-.0190	.0086	.0171	.0281
	(.0201)	(.0318)	(.0260)	(.0234)	(.0510)	(.0269)	(.0269)	(.0187)
Years since displacement	.0042	-.0045	.0118	.0159	.0053	.0199	-.0040	.0135
	(.0081)	(.0127)	(.0105)	(.0089)	(.0198)	(.0101)	(.0108)	(.0073)
Weeks Unemployed	-.0040	-.0034	-.0046	-.0020	-.0013	-.0019	-.0031	-.0039
	(.0004)	(.0007)	(.0006)	(.0006)	(.0011)	(.0007)	(.0006)	(.0004)
R^2	.15	.17	.16	.07	.19	.06	.15	.11
N	2502	1137	1365	1433	327	1106	1464	2471

Notes: The specification is as in Neal (1995); it includes year of displacement dummies and controls for changes in occupational affiliation. Standard errors are given in parentheses.

Table 5

Relative Losses for More Experienced Workers After Displacement
Neal Sample 1984-1990, with selection correction, United States Males

	E=15; T=5	E=10; T=5	E=10; T=10
INDUSTRY SWITCHER	-.2728 (.0432)	-.2249 (.0345)	-.3025 (.0408)
Industry & Skill Switcher	-.4037 (.0689)	-.3114 (.0522)	-.3617 (.0614)
Industry Switcher & Skill Stayer	-.1679 (.0563)	-.1543 (.0451)	-.2491 (.0526)
INDUSTRY STAYER	-.1022 (.0469)	-.0864 (.0371)	-.1211 (.0434)
Industry & Skill Stayer	-.0674 (.0518)	-.0608 (.0409)	-.1014 (.0476)
Industry Stayer & Skill Switcher	-.2264 (.1051)	-.1834 (.0842)	-.2360 (.0976)

Note: E is experience in years; T is firm tenure in years; standard errors in parentheses

Table 6

Determinants of Changes in Log Wages for Displaced Male Workers, 1984-1990: Selectivity Corrected Estimates

	Industry Switcher			Industry Stayer		
	All	Skill Sw	Skill St	All	Skill Sw	Skill St
Experience	-0.0149	-.0282	-.0043	-.0064	-.0178	-.0015
	(.0044)	(.0064)	(.0059)	(.0047)	(.0109)	(.0052)
Exper^2 *100	0.0212	.0388	.0062	.0130	.0368	.0006
	(.0106)	(.0152)	(.0142)	(.0090)	(.0261)	(.0120)
Tenure	-0.0215	-.0155	-.0259	-.0071	-.0073	-.0100
	(.0050)	(.0073)	(.0064)	(.0053)	(.0122)	(.0059)
Tenure^2 *100	0.0400	.0087	.0463	.0015	-.0212	.0122
	(.0179)	(.0218)	(.0230)	(.0191)	(.0495)	(.0208)
Schooling	-.0051	-.0009	-.0059	.0057	.0141	.0005
	(.0051)	(.0070)	(.0065)	(.0055)	(.0122)	(.0062)
White	-.0734	-.0428	-.0738	-.0295	.0366	-.1020
	(.0401)	(.0451)	(.0502)	(.0480)	(.0919)	(.0580)
Married	.0313	.0166	.0487	.0244	.0017	.0047
	(.0270)	(.0318)	(.0352)	(.0297)	(.0620)	(.0342)
Years since displacement	.0209	-.0045	.0281	.0136	-.0033	.0242
	(.0105)	(.0127)	(.0132)	(.0112)	(.0243)	(.0126)
Weeks Unemployed	-.0044	-.0034	-.0048	-.0024	-.0014	-.0025
	(.0005)	(.0007)	(.0007)	(.0007)	(.0012)	(.0008)
N	1653	768	885	910	224	686

Notes: The specification is as in Neal (1995); it includes year of displacement dummies and controls for changes in occupational affiliation. Standard errors are given in parentheses.

Table 7

Pre-Displacement Job Tenure and Experience and Wages:

Selectivity Corrected Estimates: US Males 1984-1990

	Full Sample	Industry Switcher			Industry Stayer		
		All	Skill Sw	Skill St	All	Skill Sw	Skill St
Experience	.0311	.0155	.0080	.0195	.0239	.0252	.0231
	(.0029)	(.0036)	(.0052)	(.0050)	(.0059)	(.0108)	(.0066)
$Exper^2$ *100	-.0596	-.0307	-.0199	-.0388	-.0389	-.0620	-.0331
	(.0079)	(.0101)	(.0145)	(.0140)	(.0155)	(.0304)	(.0173)
Tenure	.0306	.0113	.0147	.0043	.0280	.0124	.0299
	(.0035)	(.0045)	(.0065)	(.0061)	(.0073)	(.0135)	(.0082)
$Tenure^2$ *100	-.0765	-.0446	-.0539	-.0179	-.0952	-.0374	-.1028
	(.0129)	(.0162)	(.0240)	(.0218)	(.0267)	(.0549)	(.0290)
Schooling	.0710	.0714	.0484	.0829	.0709	.0574	.0766
	(.0037)	(.0046)	(.0081)	(.0061)	(.0075)	(.0132)	(.0085)
White	.1734	.1229	.1447	.1014	.1589	.1659	.1422
	(.0298)	(.0358)	(.0527)	(.0475)	(.0648)	(.0972)	(.0780)
Married	.0605	.0852	.0206	.1404	.1662	.0652	.1752
	(.0195)	(.0241)	(.0350)	(.0330)	(.0410)	(.0674)	(.0468)
Years since displacement	-	.0214	.0153	.0327	.0384	.0511	.0422
		(.0092)	(.0138)	(.0124)	(.0153)	(.0264)	(.0173)
Weeks Unemployed	-	-.0039	-.0039	-.0040	-.0024	-.0010	-.0028
		(.0005)	(.0007)	(.0006)	(.0007)	(.0014)	(.0009)
Selection Term	-	-.0238	.0128	.0707	.5346	.1500	.4777
		(.0931)	(.1173)	(.0939)	(.1237)	(.1544)	(.1403)
N	2575	1660	772	888	915	224	691

Notes: The specification is as in Neal (1995); it includes year of displacement and region of residence dummies, and industry employment growth. For the full sample the dependent variable is the pre-displacement wage. For the remaining columns the dependent variable is the post-displacement wage. Standard errors are given in parentheses.

Table 8

Effects of Pre-displacement Tenure on Post-displacement Wages:
Selectivity Corrected Estimates, United States Males 1984-1990

	E=15; T=5	E=10; T=5	E=10; T=10
INDUSTRY SWITCHER	.2088 (.0332)	.1697 (.0275)	.1928 (.0338)
Industry & Skill Switcher	.1358 (.0505)	.1206 (.0409)	.1538 (.0500)
Industry Switcher & Skill Stayer	.2226 (.0452)	.1735 (.0376)	.1816 (.0458)
INDUSTRY STAYER	.3878 (.0565)	.3167 (.0461)	.3854 (.0559)
Industry & Skill Stayer	.3959 (.0618)	.3218 (.0502)	.3942 (.0610)
Industry Stayer & Skill Switcher	.2905 (.0998)	.2422 (.0831)	.2762 (.1004)

Note: E is experience in years; T is firm tenure in years; standard errors in parentheses