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Initiative de recherche sur les compétences

Human Capital Specificity in Canada: Evidence and Implications for Policy

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Working Paper 2005 C-03

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Abstract

Increased mobility of workers across industries, occupations and firms, has implications for the labour market. Skill (or occupation) specific human capital can be used by a worker in all firms and industries. However, this is not the case for firm or industry specific human capital.

This paper presents empirical analysis on human capital specificity in Canada, using data from the 1986 Survey of Displaced Workers and the Survey of Labour and Income Dynamics. The Canadian data suggest a major role for skill (occupation) specific human capital, a modest role for firm specific human capital, largely confined to the first year of employment with a firm, and a possibly negligible role for industry specific human capital. Comparisons with the United States suggest a similar ranking of the different types of human capital in the United States. In addition, data show no evidence that the returns to specific human capital investments in the two countries are significantly different.

The evidence against industry specific human capital playing a significant role in the Canadian economy has important policy implications. An efficiently functioning labour market is continuously reallocating labour across industries in response to changing demands for different industry outputs. To the extent that only a negligible amount of human capital is industry specific, these re-allocations could take place without any major destruction of human capital, and therefore without serious negative wage consequences for the average worker, provided his basic skills are unchanged. This result could also be extended to re-allocations across narrowly defined occupations. While for the average worker the wage consequences of involuntarily moving industry may be small, the effect for a minority of individuals could be more substantial. A more disaggregated analysis would be necessary to identify such minorities.

Résumé

La mobilité accrue des travailleurs entre différents secteurs d'activités, professions et entreprises soulève des enjeux pour le marché du travail. Le capital humain spécifique aux compétences (ou à la profession), peut être utilisé par un travailleur dans toutes les entreprises et secteurs d'activité. Cependant, ceci n'est pas le cas du capital humain spécifique à l'entreprise ou au secteur d'activité.

Ce document présente une analyse empirique sur la spécificité du capital humain au Canada, à l'aide des données de l'Enquête auprès des travailleurs déplacés de 1986 et de l'Enquête sur la dynamique du travail et du revenu. Les données canadiennes montrent le rôle important joué par le capital humain spécifique relié aux compétences (à la profession), le rôle modeste du capital humain spécifique à l'entreprise, presque entièrement confiné à la première année avec l'employeur, et le rôle possiblement négligeable du capital humain spécifique au secteur d'activité. Les données américaines établissent un ordre d'importance semblable des différents types de capital humain aux États-Unis. De plus, les données ne montrent pas que les rendements des investissements en capital humain spécifique soient significativement différents dans les deux pays.

Le résultat voulant que le capital humain spécifique au secteur d'activité ne joue pas un grand rôle dans l'économie canadienne a d'importantes implications au niveau des politiques. Un marché du travail fonctionnant de manière efficiente réalloue continuellement le facteur travail entre les différents secteurs en réponse aux demandes changeantes pour les produits et services des différents secteurs. Étant donné que seule une quantité négligeable de capital humain est spécifique au secteur d'activité, ces réallocations peuvent se produire sans destruction importante de capital humain, et donc sans conséquence négative importante sur le salaire pour le travailleur moyen, si ses compétences de base restent inchangées. Ce résultat peut aussi être étendu aux réallocations entre différentes professions proches l'une de l'autre. Même si pour le travailleur moyen, les conséquences salariales de changer de secteur d'activité peuvent être faibles, l'effet pourrait être plus important pour une minorité d'individus. Une analyse plus désagrégée serait nécessaire à l'identification de telles minorités.

1 Introduction

There is an increasing consensus that in the new economy there is increasing mobility. Workers are moving at an increasing rate across firms, industries and occupations.[1] This has important implications for labour markets. The labour markets of North America are often characterized as more flexible than those of Europe. This higher degree of flexibility is one of the explanations offered for the lower unemployment rates in North America compared to Europe following the emergence of the new economy. However, the mobility of workers that creates this flexibility can also have a cost in the form of destruction of specific human capital. Human capital that is general in nature can, by definition, be used in all types of firms and production processes. A worker's general human capital is not lost when the worker moves firm, industry or occupation. Basic education is typically considered to create human capital that is largely general in this sense. Specific human capital is human capital that is useful only in certain specific settings, such as a particular firm, industry or occupation. A worker's specific human capital is of no use outside of the specific setting. It is therefore lost to the production process if the worker has to move out of the specific setting for which the human capital is useful.

[1]For recent evidence from the United States see Kambourov and Manovskii (2003).

For policy purposes it is important to know the source of human capital specificity. If a large part of a country's human capital was industry specific, then some of the gain that would occur from the reallocation of workers in a flexible labour market from declining industries to growth industries would be offset by the destruction of industry specific human capital. Large industry specific investments would in fact tend to "lock in" labour to particular industries making adjustment difficult. The same argument would apply for firm specific human capital and the reallocation of workers from declining firms to growing firms.

The literature on human capital considered at a very early stage the importance of assessing the degree of specificity. Becker (1964) focussed on the dichotomy between firm specific and general human 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 how much the time a worker spent with the same firm (firm tenure) increased earnings compared to an otherwise equivalent worker that did not stay with the same firm. 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 re-examined. In particular it has been argued that the tenure effect may be capturing industry specific capital rather than firm specific capital.[4]

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

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

[4] See Neal (1995) and Parent (2000).

In addition to the importance of specific human capital for mobility questions is the issue of the relative level of specific human capital investment. There is some debate in Canada over whether the level of worker training in Canada lags behind that of the United States. For general human capital the economics literature suggests that incentive problems would play little role in preventing the optimal amount of investment from taking place. For firm specific capital there are well known incentive problems. Evidence on the returns to specific capital in the two countries is relevant to this debate.

In this paper we present evidence on the source of specific human capital in Canada and the returns to this capital. Analysis of human capital specificity has received very little attention in Canada. In the United States literature there has been a lot of empirical work devoted to the issue using both displaced worker surveys and panel data.[5] Equivalent data sets exist in Canada, such as the 1986 Survey of Displaced Workers or the Survey of Labour and Income Dynamics but have not hitherto been exploited to examine this issue. The previous literature using data for the United States has considered primarily firm and industry specific capital.[6] Very recent unpublished work has extended this to include occupation specific capital.[7] A major hypothesis examined in this paper is that specific human capital may not be narrowly specific to a particular firm or industry setting, but may instead reside in a small number of basic skills. That is, there

[5]See for example, Abraham and Farber (1987), Altonji and Shakotko (1987), Topel (1991), Neal (1995), and Parent (2000).

[6]The most prominent recent examples are Neal (1995) and Parent (2000).

[7]See Kambourov and Manovskii (2002).

may be a small number of specific skills, such as analytic skills or fine motor skills that are useful across many firm, industry and occupation settings. If this is true it would suggest that mobility induced destruction of specific human capital could be quite small provided workers who moved did not have to move to a setting where they had to switch specific basic skills when they switched firms, industries or occupations.

The structure of the paper is as follows. In Section 2 we outline the methods used in the literature to provide evidence of specificity and distinguish between direct and indirect approaches. In Section 3 we present evidence for Canada using the indirect approach with the 1986 Survey of Displaced Workers. We then compare the results with results that we obtain from displaced worker surveys previously used in the United States literature. In order to facilitate comparison across countries, we re-analyzed the United States data sets using as close as we could get to the same estimating equations and methodology as we used for Canada rather than using existing reported results in the literature. The evidence we provide suggests that, contrary to previous results, industry specific capital may be quite small in both Canada and the United States. Instead we find evidence in favour of specific capital residing predominantly in a worker's basic skills.

The Survey of Labour and Income Dynamics is used in Section 4 as the basis for a direct approach to establishing the sources of specific human capital in Canada and estimating the returns. The results are then compared to those obtained with United States data sets using the same methodology. As with the indirect approach, the United States data sets were re-

examined both to establish as close a match as possible in estimating equations and methodology to facilitate cross country comparison and to permit the testing of additional hypotheses not previously addressed in the United States literature. The evidence from the direct approach is broadly consistent with that from the indirect approach. In addition, the results suggest that investment in firm specific human capital is quite similar in both countries. In particular, there is no evidence of less firm specific human capital in Canada. Finally, Section 5 summarizes the results and the broad policy implications.

2 Alternative Methodologies for Analyzing Specific Human Capital

Two approaches have been taken in the recent United States literature to provide evidence for the importance of industry specific capital: an indirect approach using displaced worker surveys (Neal, 1995) and a direct approach using the Panel Study of Income Dynamics (PSID) and National Longitudinal Survey of Youth (NLSY) panels (Parent, 2000). The two approaches are related. The direct approach taken by Parent if applied to displaced workers only would be equivalent to directly estimating Neal's equations (1)-(3):

$$w_1 = \alpha \text{ experience} + \theta \text{ industry tenure} + \gamma \text{ firm tenure} + X\beta + \varepsilon_1 \quad (1)$$

$$w_2 = \alpha \text{ experience} + \theta \text{ industry tenure} + X\beta + \varepsilon_2 \quad (2)$$

$$w_3 = \alpha \text{ experience} + X\beta + \varepsilon_3 \quad (3)$$

where w_1 is the wage on the pre-displacement 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. Industry tenure is the length of time the worker has been in the same industry; firm tenure is the length of time the worker has been with the same firm.[8] The interpretation of equation (1) is that a worker's wage will reflect: (i) the worker's general human capital acquired through general on the job training; (ii) the worker's industry specific human capital acquired through on the job training in a specific industry; and (iii) the worker's firm specific human capital acquired through on the job training in a specific firm. The amounts of each of these forms of human capital held by a given worker are implicitly assumed to be proportional to the amount of time spent in the relevant setting and are thus measured by years of job market experience (experience), years in the same industry (industry tenure) and years at the same firm (firm tenure). The effects of each of these forms of human capital on wages are given by the relevant coefficients, α (general human capital acquired through on the job training), θ (industry specific human capital) and γ (firm specific human capital).

[8]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 assuming that the only possible types were industry or firm specific human capital. For stayers the wage loss after displacement is less than the wage loss for switchers by the product of the effect of industry specific capital, θ, and the amount of industry specific capital as measured by years in the industry:

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

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 Displaced Worker Surveys. Instead, he estimates the following equation separately for switchers and stayers:

$$\Delta \text{lnw} = \beta_0 + \beta_1 \text{ experience} + \beta_2 \text{ experience}^2 + \beta_3 \text{ tenure} + \beta_4 \text{ tenure}^2 + Z\zeta + \varepsilon \qquad (4)$$

where Δlnw is the change in the log wage between post- and pre-displacement jobs for a worker, experience is the number of years in total job market experience that the worker had before displacement and tenure is the number of years the worker had with the same firm before

displacement. The vector Z is a set of controls.[9] 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 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.)

The specific methodology that Neal (1995) applies is to use the coefficients from equation (4) to conduct an experiment that compares the *difference* between the wage losses after displacement by experience and firm tenure for the group that switches industry to the group that does not. If industry specific capital is important, workers with more pre-displacement firm tenure and experience will suffer a larger wage loss than workers with less pre-displacement firm tenure and experience. In his specific reported experiment the "experienced" worker is displaced after 10 years with the same firm; the other worker is displaced in the first year of his career.[10] The approach is an indirect one because there is no measure of industry tenure; the qualitative effect of industry tenure is inferred from an assumed correlation between industry tenure, experience and firm tenure.

Unlike Neal (1995), Parent (2000) does take the direct approach, using the PSID and NLSY panels. His basic model is:

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

[10] Neal (1995) and Parent (2000) focus on males; for comparison purposes our analysis is also restricted to males. Although Neal (1995) argues that estimates for females may be less reliable, a full analysis should cover females as well as males.

$$\ln w_{ijkt} = \beta_0 OJ_{ijt} + \beta_1 T_{ijt} + \beta_2 Exp_{it} + \beta_3 Expind_{ikt} + \alpha_i + \theta_{ij} + \gamma_{ik} + \varepsilon_{ijt} \quad (5)$$

where w_{ijkt} is the real hourly wage of person i in job j in industry k at time t, T is firm tenure, Exp is the number of years of job market experience in total, and Expind is job market experience in the current industry.[11] Individual workers are assumed to also be different in unobservable ways and this unobserved heterogeneity is modelled as being composed of three separate components: a person specific effect representing unmeasured aspects of each individual's earning ability (α_i); a job match component representing the unmeasured quality of the employment relationship stemming from search activity (θ_{ij}); and an industry match component representing the unmeasured quality of the match between the individual and the industry in which he/she works. Unlike Neal's data set, measures of all the tenure and experience variables are directly available. However, selection effects, while possibly mitigated to some degree in Neal's displaced worker data if the displacements can be viewed as exogenous, are very likely to be present in the NLSY and PSID given the endogenous nature of job choices envisaged by standard models of worker behaviour. Parent attempts to deal with these problems via an instrumental variables (IV) methodology.[12]

[11]The α_i, θ_{ij} and γ_{ik} terms here should not be confused with the α,θ, and γ in Neal's equations (1)-(3) where they denote parameters to be estimated rather than unobserved heterogeneity.

[12]See Parent (2000) for exact details and discussion of the limitations of the approach.

Parent adds the additional variable, OJ, equal to one if firm tenure is greater than one to allow for expected non-linearities in the firm tenure effect. He also includes higher order polynomial terms in the experience and tenure variables as well as other "controls". Parent's strategy is to estimate (5) with and without the industry experience variables and note the changes to the effect of firm tenure (β_1). Having obtained a preferred specification, returns to firm and industry tenure are derived from the estimated coefficients of equation (5). Comparing the magnitude of returns then permits an assessment of the relative importance of firm and industry specific human capital.

This approach is a direct one in the sense that it uses an actual measure of industry tenure to proxy for industry specific capital in the same way that firm tenure is used to proxy firm specific capital or general work experience is used as a proxy for general human capital acquired on the job. Of course, industry tenure is not the same thing as industry specific capital any more than firm tenure is the same thing as firm specific capital. The assumption in the firm specific capital literature is that the difference in earnings between otherwise identical workers that differ only in the length of time they have been with their firm is due to the returns on firm specific investments which are correlated with the length of time a worker is with a firm. Just as all workers of the same experience level in the job market are unlikely to have acquired the same amount of general human capital from this period of time, so all workers with the same firm tenure are unlikely to have acquired the same amount of firm specific capital. The interpretation of the coefficient on firm tenure is assumed to reflect the average accumulation of firm specific capital for workers of a given level of firm tenure.

In the following sections we examine results from applying these methodologies in as comparable a way as possible to data sets for Canada and the United States. In examining the importance of skill specificity we extend the basic form of the alternative methodologies to accommodate the new hypotheses. The overall methodological approach is therefore the same as that employed in the most recent literature on human capital specificity. However, it should be noted that although these are standard approaches, they are open to a variety of forms of criticism primarily due to the endogeneity of the new job after a separation, whether the separation be in the form of displacement (indirect approach) or of any form, voluntary or involuntary (direct approach). The existing practitioners of these approaches recognize these problems and deal with them the best they can. Neal (1995) applies selection correction methods in his indirect approach and Parent (2000) uses instrumental variables to address endogeneity issues in the direct approach. Overall, however, these solutions are unlikely to be perfect and in future work it would be useful to tackle the endogeneity problem head on by modelling the endogenous job changes explicitly rather than treating the endogeneity as a nuisance to be dealt with by statistical techniques.

3 Specific Capital in Canada: Evidence from the Indirect Approach

The data set for Canada is the Survey of Displaced Workers, 1986, obtained as a supplement to the monthly Canadian Labour Force Survey. The survey month is January and the target population is persons 20 years and over. There was a sequence of questions used to

obtain the displacement information. Three questions have the same form. The person is asked if in the past 5 years he/she: " has ... been laid off from a job from which he/she was not recalled". Unfortunately the Canadian data is restricted to the 1986 survey since no further surveys were carried out. This results in a male sample size for the Canadian analysis that is smaller than can be obtained from United States data where a series of displaced worker surveys have been carried out. The smaller sample size, makes it impossible to construct an identical sample to that used by Neal. In particular, it was necessary to use all the displaced workers (except those who had an own business failure) rather than those displaced by plant closure or moving. As a check, we repeated Neal's analysis of the US data using the broader definition of displaced worker and found his results to be insensitive to the alternative definitions. In addition, the small sample size results in less precision in the estimates than is the case with the US data.

Table 1 reports the results of the indirect approach applied to the Canadian data. In the top half of the table we report the results of the methodology applied in Poletaev and Robinson (2002) to the United States data. The table reports for various sub-samples of the data set the relative wage losses for a worker that had 15 years of job market experience and 5 years of tenure with the same firm immediately prior to displacement (the "experienced" worker) compared to one that had less than a year in the labour market. In Neal's analysis the experienced worker has 10 years of total job market experience all with the same firm. The definition of the experienced worker used in Table 1 is closer to the mean values of firm tenure and job market experience in each of the sub-samples. The subsamples are distinguished by whether, after displacement, the worker switched industry or occupation.

To repeat the logic of Neal's approach to providing evidence on the presence of industry specific capital, the experienced worker by definition will be the one that has some industry or firm specific capital, if any. Since all the workers have switched firms the new wage cannot reflect any firm specific capital, but only some of the workers have switched industry. For those that have not switched industry their earnings will reflect any industry specific capital that they have. Thus in this subsample (industry stayers) the relative losses for the experienced worker after displacement should be lower. In the first row the relative wage losses are given for industry switchers, while the fourth row is for industry stayers. It is clear that, as Neal hypothesized for the United States, the relative wage losses are larger - in fact more than double - for the industry switchers in the Canadian data. This comparison appears to show that industry specific capital is important. However, as argued in Poletaev and Robinson (2002), such a conclusion may be premature.

In Poletaev and Robinson (2002) we argue that skill specificity may be more important than industry specificity and that the importance of industry specificity may be over-estimated if this is not taken into account. We specified a measure of basic skill that could be used with United States data based on the work of Ingram and Neumann (2000).[13] It was not possible to derive a comparable skill measure for use with the Canadian Survey of Displaced Workers. However, since the Ingram and Neumann measure is itself based on occupation codes, a substitute for this measure that could be applied to the Canadian data is the use of Canadian

[13] See Ingram and Neumann (2000) and Poletaev and Robinson (2002) for details.

occupational codes in the survey. The second and third rows in the upper half of Table 1 split the industry switchers into those who switch skill (occupation) and those who do not. The results are dramatic. All of the industry switcher's relative loss comes from switching skill. For example, among industry switcher's, the experienced worker's relative loss is approximately 24% if they also switch occupation but only 3% if they do not switch occupation.

If industry specificity was important and skill specificity unimportant, splitting the industry switchers into skill switchers should have shown larger losses in both the second and third rows compared to the fourth row (industry stayers). In fact this was not the case; industry stayers had larger losses than industry switchers who did not switch skill. This is further examined in the lower half of Table 1. This time the first and fourth rows contrast skill switchers and stayers, as measured by the occupation codes in the survey, while the second and third row subdivides skill switchers into industry switchers and stayers. Comparing the first and fourth row shows strong evidence of skill specific human capital. Due to the small sample size in the Canadian data set, some of the estimates have relatively large standard errors. However, the difference in this case is highly statistically significant. Moreover, unlike the upper panel of the table, the split of skill switchers into industry switchers and stayers leaves both categories of skill switchers with larger relative losses for the experienced worker than the skill stayers.[14]

[14]Basic descriptive statistics for the data set used in the regressions are given in the Appendix in Table A1. The coefficients from which the results in Table 1 were derived are presented in Tables A2 & A3. In contrasting industry switchers and stayers alone, the greater losses for the more experienced workers appear through both experience and tenure coefficients. In contrasting skill switchers and stayers the same pattern occurs.

The estimated losses reported in Table 1 are *relative* losses of the more experienced worker, not absolute losses. In fact the analysis does not attempt to measure the absolute loss. The definition of the loss is the percentage difference in the real wage of the worker some time after displacement with the real wage at the time of displacement. A variety of factors can affect this difference that should not be interpreted as a loss incurred from the displacement, including the fact that real wages would not have been constant between the time of observation of the pre-displacement and post-displacement wages. In the Canadian sample this time interval could be as much as 5 years.[15] The logic of Neal's method is that despite the difficulties inherent in estimating absolute losses for any worker, the relative losses can provide useful evidence on the source of specific human capital. Overall the evidence for the importance of industry specificity based on the Canadian data suggests that it is unimportant. There is, by contrast, consistent evidence of skill specificity, at least as far as this can be captured by the occupation proxies used in the Canadian data. If this is true, it suggests that labour mobility across industries would not be accompanied by any substantial destruction of human capital provided that these moves do not also involve skill switches.

[15]The mean post- and pre-displacement wage differences in the sample used in the regressions are reported in Table A1 in the Appendix and are in fact quite small.

Since there are many similarities between the Canadian and United States economies, evidence on the source and importance of human capital specificity from both countries can be complementary. In the remainder of this section we consider evidence based on United States data. While this is less relevant for Canada because of the source of data, it does have the advantage of a larger sample size. If the results are similar in the two countries this would increase confidence in the Canadian results that have been obtained from a relatively small sample.

The displaced worker survey data used in Neal (1995) was obtained by pooling the January 1984, 1986, 1988 and 1990 surveys that were conducted as supplements to the monthly Current Population Surveys in those months. The displacement data come from the response to the question asked of all persons 20 years and older if they had "lost or left a job because of plant closings, and employer going out of business, a layoff from which [the worker] was not recalled or other similar reasons" in the 5 years preceding the survey date. The pooled data set resulted in a sample size for men of 2641. The form of the questions is thus very similar to that of the Canadian survey and the survey month is also the same so that the two data sets appear closely comparable. The primary difference is the larger sample size in the United States data because of the series of displaced worker surveys held there compared to the single 1986 survey in Canada.

In Table 2 we report results for the United States data that are comparable to Table 1 for Canada. The United States data used in Table 2 was constructed to replicate the data set used in

Neal (1995).[16] Neal's evidence for the importance of industry specific capital can be seen in a comparison of the first and fourth rows that compared industry switchers with industry stayers. The pattern is the same as seen above in Table 1 for the Canadian data: relative losses for the experienced worker are greater for the sub-sample of industry switchers. In fact, the relative magnitudes are also similar. In both the Canadian and US data sets, the sub-sample of industry switchers shows relative losses for the experienced worker that are double the relative losses for the experienced workers in the sub-sample of industry stayers. Table 1 also showed the important result that subdividing the industry switchers into skill switchers and skill stayers, as measured by the occupation codes in the Canadian data, removes the evidence in favour of important industry specific capital. A similar exercise with the United States data does the same.

For the Canadian data we identified workers that changed basic skills with workers that changed the moderately grouped occupation codes in the Canadian Displaced Worker Survey. For the United States data we identified workers that changed basic skills with workers that moved between particular groups of occupation codes where these codes are based on the research of Ingram and Neumann (2000). Ingram and Neumann develop a measure of skill using 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

[16]We are grateful to Derek Neal for making his code available to make this possible. We use the same specification as Neal (1995) except for the omission of occupational controls. The basic pattern of results is the same with and without these controls.

Neumann (2000) use factor analysis to combine similar characteristics into a small number of broader skill characteristics.[17] We group 3-digit occupations according to the main broad skill characteristic that is used in the occupation. Changes across these groups are considered to be broad skill changes.

The results in the second and third rows of Table 2 shows that the apparent loss from switching industry is mostly due to switching basic skill. The magnitudes are not exactly comparable with the Canadian data due to the different skill measure, but the basic message is the same. In the lower half of Table 2 the same subdivision experiment is performed on skill switchers to examine whether the evidence for skill specific human capital holds up or disappears as happened for industry. The results confirm the Canadian results and the coefficients are more precisely estimated than in the Canadian data. Comparing the first and fourth rows the evidence for skill specificity is strong. The relative losses for the more experienced worker are more than twice the size for skill switchers compared to skill stayers. The subdivision of the skill switchers into industry stayers and switchers leaves this result unchanged. The subdivision results in insignificantly different coefficients for skill switchers whether they switch industry or not. In all cases they have losses approximately twice the size of skill stayers. The evidence for the importance of skill specificity thus survives the subdivision test that industry specificity failed.

[17]See Ingram and Neumann (2000) for more a detailed discussion.

Overall, the evidence using the indirect approach is consistent with the source of specificity in human capital being primarily basic skill rather than industry. The Canadian evidence is less precise because of the relatively small sample size but has the same pattern as the more precise evidence from the United States data. For both countries there is no evidence of an important degree of industry specificity to human capital. By contrast, there is evidence of basic skill specificity. Due to the indirect nature of these approaches, they do not lend themselves to quantifying the importance of specific capital in the form of estimating returns. This is one of the aims of the direct approach considered below in Section 4.

4 Specific Capital in Canada: Evidence from the Direct Approach

The direct approaches applied to United States data have used two panels: the PSID and the NLSY. The closest equivalent panel for Canada is the SLID. Given the age structure of SLID, it is closer to the PSID than to the NLSY. The major difference is the much reduced length of the SLID panel relative to the US panels. Using the SLID it is straightforward to follow the approaches of Parent (2000) and Kambourov and Manovskii (2002) (hereafter, KM) using Canadian industry and occupation codes which are constructed in a manner similar to those of the US. Thus the relative importance of firm, industry and occupation specific capital can be examined for Canada in this way. It is more difficult to assess the role of the broad skill measure because of the difficulty of comparing occupational codes across countries. The Neumann-Ingram measure is based on US census codes up to 1990. A preliminary concordance between US and Canadian SOC codes for 2000 was provided to us by the Standards Division of

Statistics Canada.[18] We have then attempted to construct the skill measure based on this concordance and our own mapping of codes from 2000 to 1990. For precise counts of detailed occupations these methods would be subject to large errors because of the substantial changes in SOC classification in the US. This classification had remained unchanged between 1980 and 1998. However, for the main skill measure the errors are likely to be much smaller as many "equivalent" occupations produced by our method that are not strictly equivalent because of the classification changes will tend to be similar in the skills they use.

Results from the SLID

Table 3, columns 1-3, show the results for Parent's basic model estimated on the SLID data using an aggregated industry coding consisting of 21 industries.[19] This is an intermediate level between the one and two digit industry codes used in the PSID which have 12 and 34 industries respectively. The industry tenure variable is constructed in the same way as Parent. The SLID , like the PSID, records the start date of the current job at the first interview but not the start date of the industry or occupation of the current job. Following Parent's strategy to overcome this missing data, industry tenure is assigned equal to firm tenure for the first interview. Thereafter, industry and occupation are recorded and, provided invalid recorded changes in industry or occupation can be eliminated, industry and occupation tenure for the remainder of the job history can be accurately constructed. The shorter length of the SLID panel

[18]We are grateful to Paul Johanis, Director of the Standards Division for making the preliminary concordance available to us. No responsibility attaches to Paul Johanis or Statistics Canada for the use we have made of their preliminary work.

[19]The industry coding used in the SLID analysis is the North American Industrial Classification System (NAICS).

may thus result in less accurate measures of industry or occupation tenure because of the larger fraction of the job history for which industry and occupation tenure have to be assigned equal to firm tenure.

Finally, the same functional form as in Parent is used. This consists of a third order polynomial for industry tenure and general experience and a combination of a dummy variable to indicate more than one year and a second order polynomial for the firm tenure variable. This form for firm tenure is generally employed in the literature and is used here for easy comparison.[20] Two definitions of tenure are used. The "continuous" measure accumulates tenure in the industry (occupation) provided almost all work was done in the same industry (occupation) in the period between interviews - i.e. the tenure in the industry/occupation was almost unbroken. This is close to Parent's measure. The non-continuous measure accumulates all work in an industry (occupation) in the worker's job history.[21]

[20]See Parent (2000) for more discussion of this functional form.

[21]Parent (2000) measures continuous industry experience as the consecutive number of years a worker has been in the same industry. If the worker ever leaves the industry to go to a new job, industry tenure is reset to zero. For non-continuous tenure it is reset to the prior level reached in the same industry as the new job. The definition used here for continuous tenure is that the level is reset to zero if less than 90% of the year was spent working in the current occupation.

In Table 3, column 1, firm tenure has a significantly positive effect. However, the main effect is from the first year dummy variable. Inclusion of continuous industry tenure (columns 2) or non-continuous industry tenure (column 3) flattens the profile of the firm tenure effect, but does not have a major impact. Moreover, the industry tenure effect itself is quite small compared to firm tenure. The magnitudes are more apparent in Table 6 where the cumulative returns are presented for the various specifications. In the first column, for example, the 2 year return for firm tenure is .0629 and the 5 year return is less than a percentage point higher at .0717, and reaches .0857 after 10 years which is only 2.3 percentage points higher than the 2 year return. Thus while there is some growth in cumulative firm tenure, the big effect occurs early on.

The introduction of industry tenure (second and third columns in Table 6) reduces the firm tenure 10 year return modestly to between .0673 to .0742, depending on the industry tenure measure, and the 10 year returns to industry tenure are themselves only in the range of .0311 to .0354. Occupation tenure is introduced in Table 3 columns 4-7. This is constructed in the same way as KM. Occupation coding changes are considered valid only if accompanied by employer changes. As with industry tenure, this could result in a downward bias for firm tenure. The introduction of occupational tenure by itself (columns 4 - 5) reduces the firm tenure effect marginally more than was the case for industry tenure and shows a significantly positive effect of occupational tenure that is substantially larger than the industry effect. In Table 6 this is reflected in, for example, 10 year returns for occupation that are double those of industry, ranging from .0671 to .0692 for occupation compared to .0311 to .0354 for industry. If both industry and occupation tenure are entered together (Table 3, columns 6 - 7), the occupation effect is further

strengthened and the industry coefficients are typically insignificantly different from zero. In Table 6 the 10 year returns to occupation range from .0605 to .1020 compared to industry returns with point estimates ranging from -.0445 to .0541.

The analysis is repeated for less aggregated industry and occupation codes in Tables 4 & 5. Table 4 uses a medium level of aggregation: the industry codes cover 105 industries and the occupation codes cover 52 occupations. Table 5 uses the most disaggregated codes of around 600 industries/occupations. The cumulative returns for industry or occupation tenure based on the more disaggregated industry/occupation codes implied by the coefficients in Tables 4 & 5 are reported in Tables 7 & 8. Introducing industry tenure by itself has increasingly larger negative effects on the firm tenure effect as the codes become more detailed, though the change remains modest. In addition, the effect of industry tenure itself gets stronger as the more detailed codes are used. The SLID data continue to show strong initial firm tenure effects after industry tenure is included, and the magnitude of the industry returns remains small. Introducing occupation at the intermediate grouping level produces similar results to Table 3. Occupational tenure by itself has significant positive returns, and when entered together with industry, the occupation returns remain the same but the industry returns disappear. The results are a little different at the most detailed coding level where all the returns are generally imprecisely estimated, and there is no longer evidence particularly favouring occupation returns over industry returns.

The basic skill measure was also analyzed using SLID, though as noted above, the construction of this measure for SLID is more complicated than for the US data sets and the

basic skill tenure variables may be subject to more measurement errors. Table 9 presents the estimated coefficients using both continuous and non-continuous measures of industry tenure and for three levels of aggregation of industry codes. Column 1 re-presents the estimates including only firm tenure for ease of comparison, showing significant effects of firm tenure, including growth in returns after the first year. Including skill tenure removes the growth in firm tenure returns and shows significant skill tenure returns. Including industry tenure as well as skill and firm tenure results in generally insignificant coefficients for industry tenure and significantly positive coefficients for skill tenure. The relevant magnitudes are more apparent in Table 10 which reports the cumulative returns to firm, industry and skill tenure. The first two columns of Table 10 report the returns for the specification which includes just firm and skill tenure. Skill tenure by itself completely flattens the firm tenure profile. The cumulative returns for 2 or 10 years are the same. This is in contrast to the results in Tables 6-8 for industry and occupation where in many cases the firm tenure profile remains increasing. The cumulative returns to skill are increasing and in the non-continuous case surpass the firm tenure returns around 7 years.

The remaining columns of Table 10 report the returns for the specification that includes firm, industry and skill tenure together. The returns are presented for three levels of industry aggregation. The firm returns remain similar, though in the continuous tenure case, evidence of an increasing cumulative return to firm tenure re-appears. Comparing industry and skill tenure, using the continuous measure industry returns are insignificantly different from zero and the skill returns are significantly positive, increasing, and larger than firm returns after the first 5-7 years. Using the non-continuous measure, skill returns are again significantly positive and large

relative to firm effects after 5-7 years. Industry returns remain insignificantly different from zero except for the most disaggregated case (penultimate column) where the magnitude is surpassed by the skill return at about 8 years. Comparing the skill results with those for occupation in Tables 6-8, the skill returns are generally much steeper and typically by 10 years show larger returns than for occupation. The skill return patterns are consistent across the levels of aggregation for industry tenure.[22]

Overall, the SLID results show an important role for the skill measure. They are consistent with the results based directly on the Canadian occupation codes. Thus for Canada, the evidence for the importance of basic skill specific human capital over industry specific human capital is strong.[23] The estimates suggest a magnitude of ten year returns to skill tenure around 10%. In addition, the Canadian evidence shows evidence of firm specific capital even when industry, occupation or skill measures are taken into account, though the magnitude is modest and the investment is largely confined to the first year with a firm.

[22]The skill definition is based on a single occupational aggregation level - an approximation to the 3-digit U.S. codes, while occupational tenure depends on the level of aggregation of the codes. Skill returns are therefore less likely to vary across levels of aggregation than occupation returns.

[23]To the extent that the estimates are subject to the same sensitivity regarding the assumptions used to identify valid industry and occupation switches, and given the difficulty of constructing the skill measure for Canada, the results should be interpreted with some caution.

Results from US Panels

The Canadian evidence is based on a relatively short panel. By contrast, the United States evidence comes from the much longer PSID and NLSY panels. It is therefore of use to compare the Canadian and United States evidence both to assess whether the both countries data sets identify the same sources of specificity and to examine whether the Canadian returns for the various forms of specific human capital are similar to those of the United States. The most recent evidence from the United States panels comes from Parent (2000) and Kambourov and Manovskii (2002). Parent (2000) tests whether specific human capital is firm specific or industry specific. Parent estimates equation (5) with and without industry variables. In all cases of estimation technique and industry definition, and across both the NLSY and PSID data sets, Parent shows that inclusion of the industry experience variables greatly reduces the firm tenure effect which, in the IV estimates, becomes insignificantly different from zero. The industry tenure variable remains significant. The results of Kambourov and Manovskii (2002), however, cast substantial doubt on the importance of industry tenure in favour of occupation tenure.

We obtained a sample from the NLSY as close as possible to that used by Parent. Using this sample we were able to closely approximate the results of Parent (2000) for the baseline regression that estimates the simple firm tenure effect with no other tenure variables included. We also obtained qualitatively the same result as Parent when industry tenure was included. Firm tenure becomes insignificant in all cases and industry tenure has significantly positive returns. The introduction of the basic skill measure has a similar effect to introducing industry tenure. Evidence of firm tenure is again eliminated and basic skill tenure has significantly positive

returns. Including firm, industry and skill tenure together shows again no return to firm tenure and about equal positive returns to skill and industry tenure except for the three-digit continuous case where industry returns are insignificant.[24] Overall, our analysis of the direct approach using NLSY data provides substantial evidence of the importance of the basic skill tenure which is consistent with the SLID results. However, the age structure of the NLSY panel makes direct comparison with the SLID results difficult. A better comparison can be made between the PSID and SLID results since both panels have similar age structures.

Parent's analysis of the PSID uses data only for the period 1981-91. In contrast with the NLSY, this presents a problem of measurement for industry tenure for workers who have been employed before 1981. Parent's solution is to assign the reported firm tenure in 1981 as equivalent to industry tenure. In addition, Parent assumes that recorded industry changes that are not accompanied by firm changes are invalid. An additional problem for the direct approach, stemming from the panel data nature of the data used, is the bias induced by measurement error in the job histories. It is well recognized in the literature that the data sets employed by Parent - the PSID and NLSY - have problems in this regard that complicate the computation of accurate firm, industry or occupation tenure variables.[25] A procedure based on Brown and Light (1992) to distinguish true from false changes in firm or industry (Partition T) is employed in Parent (2000) and Kambourov and Manovskii (2002). In essence this involves identifying a firm switch when the reported length of employment at a given firm is smaller than the time elapsed since

[24]See Poletaev and Robinson (2003) for a full analysis of the NLSY.

[25]See in particular Brown and Light (1992).

the last interview and only counting an industry or occupation code change as valid if it is accompanied by a firm switch defined in this way.

The PSID has also been analysed by KM, using the same time period as Parent, but utilizing the newly available retrospective PSID data which were obtained by having industry and occupation recoded by a single person across all observations for the same individual. This recoding dramatically reduced the number of switches especially for occupation. The results of KM support Parent's conclusion of insignificant firm tenure effects but cast substantial doubt on the importance of industry tenure in favour of occupation tenure. KM examine various methods of identifying true occupation (industry) switches. KM use an approach based on Brown and Light (1992) to calculate firm tenure and follow Parent in not permitting an industry change unaccompanied by an employer change. In addition, they apply the same rule for occupations. While applying the rule for industry changes appears in the literature to be relatively uncontroversial there has not previously been made a case for applying it to occupations since it rules out career ladders within firms. KM make the case that without this restriction, occupation tenure will remain too noisy.

We have repeated Parent's analysis using the data of Kambourov and Manovskii (2002) including a measure of main skill tenure and again the evidence for industry specific capital is substantially reduced. These data are similar to those of Parent and can replicate the basic features of Parent's results. KM identify industry and occupation switches up to 1980 using the Retrospective File information. After 1980 switches are identified from applying variations on

Partition T to identify firm tenure and requiring genuine industry or occupation changes to be accompanied by employer changes. The availability of the Retrospective File permit a more accurate calculation of industry or occupation tenure prior to 1981 than was possible for Parent who had to assign industry tenure for all those present in the panel in 1981 as identically equal to firm tenure.[26]

The estimated coefficients of the earnings functions are given in Tables 11 (one-digit) & 12 (three-digit). The estimated returns are reported in Table 13. Without any industry or skill tenure variables a significant positive firm tenure effect is estimated (Table 13, column 1). The coefficients on the dummy variable equal to one if firm tenure is greater than one year and on the quadratic terms for firm tenure are in fact quite similar to those of Parent (2000). Adding the continuous industry tenure variables (column 2 in Tables 11 & 12) reduces the firm tenure effect - halving it in the one-digit case - and results in significant industry tenure returns of a very similar magnitude to those of Parent (2000) for the one digit case, though substantially smaller for the three-digit case.[27] The industry tenure is calculated in the same way as in Parent (2000) which does not permit an industry change without a firm change. However, unlike Parent (2000), the firm tenure effect remains significant. This may be due to the fact that the use of the

[26]See Kabourov and Manovskii (2002) for a detailed discussion of the sample construction and the relation to Parent's sample.

[27]For the one-digit result, by comparison, the coefficients in Parent (2000) for the linear, quadratic and cubic terms for industry tenure are .0211, -.11 and .0021 versus .0191, -.10 and .0014 in Table 11 results. The cumulative returns for 2, 5 and 10 years are .0348, .0742 and .1077 in Table 13 compared to .0378, .0792 and .1144 in Parent's Table 3.

retrospective files to calculate initial industry tenure instead of setting it equal to firm tenure as in Parent (2000) reduces the correlation between firm and industry tenure.

Comparison of Canadian and US Results

Comparison of these PSID results with those from the SLID shows considerable qualitative similarity, though there are interesting differences, especially in the behaviour of the firm tenure effect. When firm tenure is considered by itself the cumulative returns are 6.29% at 2 years, 7.17% at 5 years and 8.57% at 10 years. The magnitude of the 10 year return is similar to the PSID estimates obtained by both Parent and KM, but the time path of the return is different. In particular, the SLID estimates always show a much larger return to the first year, and then slower growth in the cumulative returns thereafter compared to the PSID.

The introduction of industry tenure in the SLID results in most cases reduces the firm tenure effects only modestly and shows quite low cumulative returns to industry tenure even after 10 years. In the SLID estimates the results are obtained at three different levels of industry aggregation and for both continuous and non-continuous definitions of industry tenure. The industry aggregation levels are not strictly comparable across the data sets. Our analysis of the SLID data used three levels of industry aggregation. The first (high) aggregation consists of 21 industries. This is an intermediate level between the one and two digit industry codes used in the PSID which have 12 and 34 industries respectively. The second is a medium level of aggregation: the industry codes cover 105 industries and the occupation codes cover 52 occupations. The industry code is thus between the 2 and 3 digit codes used in the PSID which

contain 34 and 213 industries, respectively. The occupation codes are also between the PSID 2 and 3 digit codes which contain 26 and 428 occupations, respectively. Table 3 uses the most disaggregated codes of around 600 industries/occupations - a more disaggregated level than the 3 digit level used by the PSID.

In all levels of aggregation with continuous definition of industry tenure, and in all but the lowest level of aggregation with the non-continuous definition of industry tenure the introduction of industry tenure in the SLID results reduces the firm tenure effects only modestly and shows quite low cumulative returns to industry tenure even after 10 years. This contrasts with the PSID results reported by Parent, though it is closer to the PSID results obtained using the KM data set. In Parent (2000) the firm effect is always at least halved by the introduction of industry and the industry effect itself is always more than double the SLID estimates. Using the KM data set the firm effect is reduced by nearly one half in the one-digit case, but much less in the two-digit case and only marginally in the three digit case. In addition, in KM the 10 year industry returns are smaller - as low as 5% in the three-digit case. Only in the lowest aggregation with the non-continuous definition of industry tenure is the firm effect substantially changed by the introduction of industry tenure in the SLID.

The introduction of occupation or skill tenure in the SLID analysis largely eliminated any evidence of industry specific capital. KM report the same for their analysis of the PSID using occupation. Our analysis of the KM data using the skill measure has a similar result. In most cases industry tenure is insignificant, or if statistically significant it is of small magnitude. Only

the results using the 1-digit codes produce a ten year cumulative return for industry above 5%. By contrast, consistently in both the SLID and PSID results, the ten year cumulative returns to skill are substantially above 5%. Apart from eliminating any significant evidence of industry specific human capital, the other consistent result of introducing a skill measure in the SLID analysis is the flattening of the estimated firm tenure profile. This is not the case for the PSID results. However the United States results from the PSID do show the same relative ranking of firm and skill tenure and a similar 10 year cumulative returns across the two countries.

5 Summary and Policy Implications

This paper has presented evidence on human capital specificity in Canada using the 1986 Survey of Displaced Workers and the Survey of Labour and Income Dynamics. The evidence was derived using two methodological approaches previously applied to United States data: the indirect approach using displaced worker surveys, and the direct approach using panel data. The Canadian evidence produced from the indirect approach in Section 3 suggests that any specificity of human capital in Canada is more likely to be related to basic skill than to industry. Comparison with results using the same analysis with United States data yields the same conclusion. In both countries the evidence is consistent with the importance of basic skill specificity relative to industry specificity. Indeed, there is little evidence of any industry specific capital when basic skill specific capital is taken into account. The indirect approach is useful for identifying sources of specificity, but not for assessing relative returns to different types of specific capital.

Evidence derived from the Survey of Labour and Income Dynamics on the relative importance of firm, industry and basic skill specific human capital using the direct approach suggests a major role for skill specific capital, a modest role for firm specific capital, largely confined to the first year of employment with a firm, and a possibly negligible role for industry specific capital in the Canadian labour market. Comparison with the Panel Study of Income Dynamics results for the United States shows a similar ranking for both countries. In addition, there is no evidence that the returns to specific human capital investments in the two countries are significantly different.

KM's analysis of the PSID concludes with the finding that if occupational tenure is taken into account, there is little importance for industry tenure in explaining wages. They argue that this conclusion has intuitive appeal. The industry codes were not designed to reflect primarily the tasks performed by workers. "While it is true that the work setting (industry) can affect the job one performs, it seems implausible that the human capital of these workers is specific to the industry they work in rather than to the type of work they do (their occupation).. ...it appears natural to expect that when a truck driver switches industries (say, from wholesale trade to retail trade)....he loses less of his human capital generated by the truck-driving experience than when he switches his occupation and becomes a cook."[28] The argument for the importance of basic skill takes this argument one step further. The occupation codes include a wide range of distinct occupations some of which use very different skills, say heavy lifting occupations versus manual

[28]Kambourov and Manovskii (2002), p 2.

dexterity occupations, and others that use the same or very similar skills, say managerial occupations that appear in the classifications as different occupations. They also include, in some cases, progression levels in a given skill such as automobile mechanic apprentice and automobile mechanic. Presumably, the human capital learned as an automobile mechanic apprentice should not all be lost when a worker changes occupation to become an automobile mechanic.

The evidence against industry specific capital playing a significant role in the Canadian economy has important policy implications. An efficiently functioning labour market is continuously reallocating labour across industries in response to changing demands for different industry outputs. To the extent that only a negligible amount of human capital is industry specific, these re-allocations could take place without any major destruction of human capital, and therefore without serious negative wage consequences for the average worker, provided the same basic skills are unchanged. Although the evidence suggests that industry specific capital may be relatively unimportant, it does not mean that it is unimportant for all workers. While for the average worker the wage consequences of involuntarily moving industry may be small, the effect for a minority of individuals could be more substantial. A more disaggregated analysis would be necessary to identify such minorities.

There is evidence from the Canadian data sets that any specific human capital of Canadian workers may not be narrowly specific, but instead may be specific to a small number of basic skills. To the extent that this is true, the probable absence of negative wage effects from labour market re-allocation patterns in response to changing industry demands could be

extended to re-allocation across narrowly defined occupations, provided the re-allocations did not require any change in basic skills. In view of the increased labour market mobility in the new economy, this suggests that the required re-allocations may take place without great wage cost to the average worker, though again it is possible that large losses could occur for small groups of workers.

Comparison of the estimates of the cumulative returns to firm and skill tenure for Canada and the United States show no generally significant differences across countries. These estimates are obtained from the direct approach applied to panel data that contain measures of firm and occupation tenure. These estimates, as discussed in Section 2, reflect the returns averaged across all workers of a given tenure, and therefore the specific human capital averaged across all workers of a given tenure. If the per-worker returns to a specific human capital investment were the same in both countries but Canadian workers had on average lower investments, under the direct approach methodology the estimates of the cumulative returns would be lower for Canada. In fact, for both firm and skill tenure there is no systematic difference between the countries evident in Tables 10 and 13.

Empirical research on skill based specificity is still in a very early stage. There remain many gaps in our knowledge. We would argue that the skill specificity is unlikely to be as narrowly defined as the United States 3-digit occupations codes as studied in KM. Not only would this rule out the skills of the automobile mechanic apprentice being useful to him/her when he/she changes 3-digit occupation to become an automobile mechanic, it would also rule

out career paths across occupations where the skills acquired along the way are precisely those required for the terminal point of the path. The former is to some extent accounted for in our basic skill measure, but the latter is not. Future work that studied career paths and their evolving skill mixes in a model of endogenous worker mobility could usefully increase our knowledge of the labour market's ability to adapt to future changes without major negative wage consequences for Canadian workers.

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Table 1
Relative Losses for More Experienced Workers After Displacement: Canada Males

By Industry Status

	Relative Loss	Standard Error
Industry Switcher	-0.2061	0.0564
Industry & Occupation Switcher	-0.2351	0.0645
Industry Switcher & Occupation Stayer	-0.0266	0.1108
Industry Stayer	-0.0872	0.0708

By Occupation Status

	Relative Loss	Standard Error
Occupation Switcher	-0.231	0.0589
Occupation & Industry Switcher	-0.2351	0.0645
Occupation Switcher & Industry Stayer	-0.2281	0.1623
Occupation Stayer	0.0183	0.0576

Notes:
1. The more experienced worker has 15 years of job market experience and 5 years of tenure with the same firm just prior to displacement. These values are close to the mean values for all the sub-samples.
2. The results are based on a quadratic specification for experience and tenure and do not include Neal's occupation controls. The basic results are insensitive to the inclusion of these controls.

Table 2
Relative Losses for More Experienced Workers After Displacement: Neal Sample 1984-1990, United States Males

By Industry Status

	Relative Loss	Standard Error
Industry Switcher	-0.2462	0.0344
Industry & Skill Switcher	-0.3339	0.0509
Industry Switcher & Skill Stayer	-0.1806	0.0477
Industry Stayer	-0.1193	0.0409

By Skill Status

	Relative Loss	Standard Error
Skill Switcher	-0.313	0.044
Skill & Industry Switcher	-0.3339	0.0509
Skill Switcher & Industry Stayer	-0.2727	0.0889
Skill Stayer	-0.1272	0.0274

Notes:
1. The more experienced worker has 15 years of job market experience and 5 years of tenure with the same firm just prior to displacement. These values are close to the mean values for all the sub-samples.
2. The results are based on a quadratic specification for experience and tenure and exclude Neal's occupation controls. The basic results are insensitive to the inclusion of these controls.

Table 3: SLID Earnings Function Estimates: high aggregation

	1	2	3	4	5	6	7
		C	NC	C	NC	C	NC
Old Job	.0569	.0492	.0488	.0473	.0464	.0478	.0467
	(.0062)	(.0064)	(.0063)	(.0064)	(.0068)	(.0064)	(.0070)
Firm	.0030	.0018	.0038	-.0024	.0036	-.0012	.0012
	(.0014)	(.0035)	(.0024)	(.0033)	(.0026)	(.0035)	(.0029)
Firm(2)	-.0000	-.0000	-.0001	.0002	-.0001	.0001	-.0001
	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)
Industry		.0090	.0091			-.0154	.0033
		(.0039)	(.0031)			(.0082)	(.0052)
Ind(2)		-.0007	-.0007			.0013	.0003
		(.0002)	(.0002)			(.0006)	(.0004)
Ind(3)x100		.0015	.0017			-.0023	-.0009
		(.0003)	(.0003)			(.0012)	(.0009)
Occupation				.0162	.0145	.0293	.0158
				(.0038)	(.0033)	(.0081)	(.0052)
Occ(2)				-.0011	-.0010	-.0023	-.0013
				(.0002)	(.0002)	(.0006)	(.0004)
Occ(3)x100				.0019	.0022	.0041	.0030
				(.0003)	(.0004)	(.0012)	(.0009)
Experience	.0454	.0410	.0384	.0399	.0474	.0392	.0476
	(.0041)	(.0042)	(.0043)	(.0042)	(.0040)	(.0042)	(.0041)
Exp(2)	-.0016	-.0016	-.0016	-.0015	-.0013	-.0016	-.0014
	(.0001)	(.0001)	(.0001)	(.0001)	(.0002)	(.0001)	(.0002)
Exp(3)x100	.0018	.0017	.0016	.0016	.0013	.0016	.0014
	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)

Notes: standard errors in parentheses; C denotes continuous tenure; NC denotes non-continuous.

Table 4: SLID Earnings Function Estimates: medium aggregation

	1	2	3	4	5	6	7
		C	NC	C	NC	C	NC
Old Job	.0569	.0487	.0477	.0467	.0454	.0477	.0458
	(.0062)	(.0065)	(.0063)	(.0064)	(.0067)	(.0064)	(.0070)
Firm	.0030	.0011	.0041	-.0043	.0022	-.0034	.0005
	(.0014)	(.0042)	(.0026)	(.0036)	(.0027)	(.0040)	(.0032)
Firm(2)	-.0000	.0000	-.0001	.0003	-.0000	.0002	-.0000
	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)
Industry		.0105	.0089			-.0148	-.0004
		(.0046)	(.0032)			(.0093)	(.0051)
Ind(2)		-.0008	-.0008			.0017	.0004
		(.0002)	(.0002)			(.0006)	(.0004)
Ind(3)x100		.0015	.0019			-.0027	-.0011
		(.0003)	(.0003)			(.0011)	(.0008)
Occupation				.0187	.0161	.0314	.0193
				(.0041)	(.0033)	(.0086)	(.0052)
Occ(2)				-.0013	-.0012	-.0028	-.0016
				(.0002)	(.0002)	(.0006)	(.0004)
Occ(3)x100				.0020	.0024	.0046	.0034
				(.0003)	(.0004)	(.0012)	(.0009)
Experience	.0454	.0438	.0390	.0407	.0458	.0391	.0478
	(.0041)	(.0041)	(.0042)	(.0041)	(.0040)	(.0042)	(.0041)
Exp(2)	-.0016	-.0015	-.0015	-.0015	-.0013	-.0015	-.0013
	(.0001)	(.0001)	(.0001)	(.0001)	(.0002)	(.0001)	(.0002)
Exp(3)x100	.0018	.0016	.0015	.0015	.0013	.0016	.0013
	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)

Notes: standard errors in parentheses; C denotes continuous tenure; NC denotes non-continuous.

Table 5: SLID Earnings Function Estimates: low aggregation

	1	2	3	4	5	6	7
		C	NC	C	NC	C	NC
Old Job	.0569	.0483	.0470	.0457	.0451	.0467	.0457
	(.0062)	(.0065)	(.0065)	(.0065)	(.0064)	(.0065)	(.0063)
Firm	.0030	.0001	-.0009	-.0005	.0031	-.0013	-.0006
	(.0014)	(.0046)	(.0029)	(.0040)	(.0029)	(.0043)	(.0034)
Firm(2)	-.0000	.0001	.0001	.0001	-.0000	.0002	.0001
	(.0001)	(.0002)	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)
Industry		.0118	.0168			-.0097	.0081
		(.0050)	(.0035)			(.0111)	(.0049)
Ind(2)		-.0009	-.0011			.0012	-.0003
		(.0002)	(.0002)			(.0007)	(.0004)
Ind(3)x100		.0016	.0021			-.0034	.0003
		(.0003)	(.0003)			(.0014)	(.0007)
Occupation				.0149	.0121	.0244	.0084
				(.0045)	(.0034)	(.0105)	(.0048)
Occ(2)				-.0012	-.0011	-.0023	-.0009
				(.0002)	(.0002)	(.0007)	(.0004)
Occ(3)x100				.0021	.0023	.0052	.0020
				(.0003)	(.0003)	(.0014)	(.0007)
Experience	.0454	.0439	.0426	.0423	.0391	.0411	.0382
	(.0041)	(.0041)	(.0041)	(.0041)	(.0042)	(.0042)	(.0043)
Exp(2)	-.0016	-.0015	-.0014	-.0015	-.0015	-.0015	-.0015
	(.0001)	(.0001)	(.0001)	(.0001)	(.0002)	(.0001)	(.0002)
Exp(3)x100	.0018	.0016	.0015	.0015	.0015	.0016	.0016
	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)

Notes: standard errors in parentheses; C denotes continuous tenure; NC denotes non-continuous.

Table 6: SLID Cumulative Returns to Firm, Industry and Occupation Tenure: high aggregation

	Firm	Firm & Industry		Firm & Occupation		Firm, Industry & Occupation		
		Firm	Industry	Firm	Occup	Firm	Industry	Occup
Continuous								
2	.0629	.0528	.0152	.0431	.0279	.0459	-.0257	.0497
	(.0055)	(.0082)	(.0072)	(.0080)	(.0069)	(.0083)	(.0146)	(.0143)
5	.0717	.0583	.0285	.0464	.0548	.0445	-.0467	.0937
	(.0063)	(.0148)	(.0155)	(.0176)	(.0150)	(.0150)	(.0306)	(.0297)
10	.0857	.0673	.0311	.0537	.0671	.0462	-.0445	.1020
	(.0089)	(.0238)	(.0244)	(.0289)	(.0234)	(.0240)	(.0476)	(.0455)
Non-continuous								
2	.0629	.0559	.0154	.0531	.0253	.0487	.0077	.0267
	(.0055)	(.0062)	(.0055)	(.0069)	(.0059)	(.0073)	(.0089)	(.0088)
5	.0717	.0646	.0293	.0615	.0509	.0504	.0229	.0508
	(.0063)	(.0093)	(.0117)	(.0103)	(.0125)	(.0115)	(.0173)	(.0171)
10	.0857	.0742	.0354	.0709	.0692	.0498	.0541	.0605
	(.0089)	(.0138)	(.0181)	(.0154)	(.0190)	(.0175)	(.0227)	(.0220)

Notes: standard errors in parentheses

Table 7: SLID Cumulative Returns to Firm, Industry and Occupation Tenure: medium aggregation

	Firm	Firm & Industry		Firm & Occupation		Firm, Industry & Occupation		
		Firm	Industry	Firm	Occup	Firm	Industry	Occup
Continuous								
2	.0629	.0510	.0178	.0393	.0323	.0416	-.0231	.0520
	(.0055)	(.0094)	(.0084)	(.0085)	(.0074)	(.0092)	(.0167)	(.0153)
5	.0717	.0550	.0343	.0325	.0635	.0351	-.0351	.0926
	(.0063)	(.0178)	(.0184)	(.0155)	(.0162)	(.0172)	(.0356)	(.0322)
10	.0857	.0630	.0401	.0326	.0772	.0313	-.0055	.0790
	(.0089)	(.0287)	(.0294)	(.0249)	(.0256)	(.0279)	(.0566)	(.0503)
Non-continuous								
2	.0629	.0555	.0145	.0497	.0279	.0468	.0007	.0327
	(.0055)	(.0065)	(.0058)	(.0069)	(.0060)	(.0076)	(.0088)	(.0088)
5	.0717	.0657	.0256	.0556	.0549	.0481	.0066	.0620
	(.0063)	(.0103)	(.0122)	(.0108)	(.0126)	(.0128)	(.0173)	(.0172)
10	.0857	.0790	.0232	.0641	.0696	.0501	.0250	.0718
	(.0089)	(.0154)	(.0185)	(.0163)	(.0192)	(.0195)	(.0228)	(.0224)

Notes: standard errors in parentheses

Table 8: SLID Cumulative Returns to Firm, Industry and Occupation Tenure: low aggregation

	Firm	Firm & Industry		Firm & Occupation		Firm, Industry & Occupation		
		Firm	Industry	Firm	Occup	Firm	Industry	Occup
Continuous								
2	.0629	.0489	.0200	.0452	.0253	.0446	-.0148	.0399
	(.0055)	(.0101)	(.0092)	(.0093)	(.0082)	(.0097)	(.0201)	(.0189)
5	.0717	.0517	.0378	.0464	.0480	.0441	-.0224	.0704
	(.0063)	(.0197)	(.0203)	(.0176)	(.0181)	(.0187)	(.0434)	(.0405)
10	.0857	.0613	.0416	.0537	.0534	.0497	-.0091	.0641
	(.0089)	(.0321)	(.0326)	(.0289)	(.0293)	(.0306)	(.0696)	(.0650)
Non-continuous								
2	.0629	.0455	.0292	.0512	.0201	.0449	.0149	.0134
	(.0055)	(.0070)	(.0062)	(.0070)	(.0062)	(.0075)	(.0084)	(.0083)
5	.0717	.0447	.0581	.0596	.0362	.0448	.0322	.0225
	(.0063)	(.0116)	(.0132)	(.0117)	(.0131)	(.0133)	(.0166)	(.0165)
10	.0857	.0472	.0746	.0716	.0350	.0479	.0491	.0164
	(.0089)	(.0173)	(.0199)	(.0179)	(.0200)	(.0205)	(.0219)	(.0220)

Notes: standard errors in parentheses

Table 9: SLID Earnings Function Estimates with Basic Skill Measure

	1	2	3	4	5	6	7	8	9
		C	NC	C	NC	C	NC	C	NC
Industry Aggregation				high		medium		low	
Old Job	.0569	.0576	.0579	.0494	.0495	.0491	.0485	.0487	.0477
	(.0062)	(.0062)	(.0083)	(.0064)	(.0067)	(.0066)	(.0070)	(.0066)	(.0072)
Firm	.0030	-.0023	-.0014	.0013	.0011	.0023	.0014	.0035	-.0031
	(.0014)	(.0029)	(.0030)	(.0035)	(.0026)	(.0044)	(.0030)	(.0050)	(.0034)
Firm(2)	-.0000	.0002	.0001	.0000	-.0000	.0000	-.0000	.0001	.0001
	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)	(.0002)	(.0001)	(.0002)	(.0001)
Industry				-.0113	.0052	-.0039	.0059	-.0037	.0138
				(.0073)	(.0036)	(.0078)	(.0037)	(.0083)	(.0041)
Ind(2)				.0000	-.0005	-.0003	-.0007	-.0005	-.0010
				(.0003)	(.0002)	(.0003)	(.0002)	(.0003)	(.0002)
Ind(3)x100				.0017	.0018	.0017	.0020	.0017	.0021
				(.0003)	(.0004)	(.0003)	(.0004)	(.0003)	(.0004)
Skill		.0061	.0097	.0226	.0098	.0146	.0094	.0137	.0083
		(.0027)	(.0034)	(.0059)	(.0030)	(.0054)	(.0030)	(.0052)	(.0031)
Skill(2)		-.0002	-.0001	-.0009	-.0003	-.0006	-.0002	-.0004	-.0002
		(.0001)	(.0001)	(.0002)	(.0001)	(.0002)	(.0001)	(.0002)	(.0001)
Skill(3)x100		.0000	-.0000	-.0000	-.0000	-.0000	-.0000	-.0000	-.0000
		(.0000)	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)
Experience	.0454	.0440	.0483	.0389	.0384	.0439	.0393	.0441	.0411
	(.0041)	(.0041)	(.0052)	(.0042)	(.0045)	(.0040)	(.0046)	(.0040)	(.0046)
Exp(2)	-.0016	-.0016	-.0016	-.0015	-.0015	-.0015	-.0015	-.0015	-.0015
	(.0001)	(.0001)	(.0002)	(.0001)	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)
Exp(3)x100		.0017	.0018	.0016	.0015	.0015	.0015	.0015	.0015
		(.0002)	(.0003)	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)

Notes: Standard errors in parentheses. C denotes continuous tenure; NC denotes non-continuous tenure.

Table 10: SLID Cumulative Returns to Firm, Industry and Skill Tenure.

	Firm & Skill		Firm, Industry & Skill			Firm, Industry & Skill			Firm, Industry & Skill		
			high aggregation			medium aggregation			low aggregation		
	Firm	Skill	Firm	Ind	Skill	Firm	Ind	Skill	Firm	Ind	Skill
Continuous											
2	.0537	.0114	.0521	-.0224	.0416	.0539	-.0086	.0268	.0561	-.0093	.0258
	(.0071)	(.0051)	(.0083)	(.0137)	(.0111)	(.0099)	(.0147)	(.0101)	(.0109)	(.0156)	(.0097)
5	.0508	.0253	.0569	-.0540	.0907	.0614	-.0239	.0582	.0681	-.0291	.0584
	(.0120)	(.0115)	(.0151)	(.0309)	(.0251)	(.0191)	(.0334)	(.0230)	(.0218)	(.0353)	(.0221)
10	.0534	.0400	.0667	-.0947	.1363	.0749	-.0486	.0867	.0910	-.0710	.0965
	(.0190)	(.0191)	(.0245)	(.0524)	(.0425)	(.0314)	(.0568)	(.0392)	(.0361)	(.0598)	(.0374)
Non-continuous											
2	.0556	.0188	.0515	.0084	.0185	.0512	.0091	.0179	.0420	.0237	.0160
	(.0079)	(.0065)	(.0067)	(.0064)	(.0056)	(.0073)	(.0067)	(.0056)	(.0079)	(.0073)	(.0058)
5	.0537	.0450	.0538	.0148	.0418	.0548	.0142	.0413	.0354	.0461	.0374
	(.0117)	(.0147)	(.0104)	(.0137)	(.0126)	(.0118)	(.0144)	(.0127)	(.0133)	(.0156)	(.0130)
10	.0549	.0830	.0557	.0156	.0690	.0596	.0079	.0708	.0298	.0567	.0662
	(.0174)	(.0250)	(.0157)	(.0210)	(.0208)	(.0179)	(.0217)	(.0212)	(.0201)	(.0234)	(.0219)

Table 11: PSID Industry vs Firm vs Skill Effects, IV-GLS (One Digit)

	(1)	(2)	(3)	(4)
OldJob	.0184	.0097	.0098	.0048
	(.0094)	(.0100)	(.0096)	(.0100)
Firm	.0083	.0044	.0057	.0032
	(.0018)	(.0022)	(.0019)	(.0022)
Firm(2)	-.0001	.0000	-.0000	.0000
	(.0001)	(.0001)	(.0001)	(.0001)
Industry		.0191		.0154
		(.0034)		(.0036)
Ind(2)		-.0010		-.0008
		(.0002)		(.0002)
Ind(3)x100		.0014		.0011
		(.0004)		(.0004)
Skill			.0231	.0155
			(.0044)	(.0047)
Skill(2)			-.0018	-.0012
			(.0004)	(.0004)
Skill(3)x100			.0042	.0032
			(.0011)	(.0011)
Experience	.0798	.0467	.0712	.0499
	(.0086)	(.0054)	(.0087)	(.0060)
Exp(2)	-.0012	-.0008	-.0011	-.0008
	(.0002)	(.0002)	(.0002)	(.0002)
Exp(3)x100	.0011	.0004	.0010	.0007
	(.0002)	(.0003)	(.0003)	(.0003)

Table 12: PSID Industry vs Firm vs Skill Effects, IV-GLS (Three Digits)

	(1)	(2)	(3)	(4)
Old Job	.0162	-.0099	.0071	.0041
	(.0091)	(.0096)	(.0095)	(.0097)
Firm	.0077	.0061	.0056	-.0057
	(.0018)	(.0026)	(.0019)	(.0026)
Firm(2)	-.0001	-.0000	-.0000	-.0000
	(.0001)	(.0001)	(.0001)	(.0001)
Industry		.0120		.0055
		(.0035)		(.0037)
Ind(2)		-.0008		-.0005
		(.0002)		(.0002)
Ind(3)x100		.0013		.0008
		(.0004)		(.0004)
Skill			.0237	.0202
			(.0044)	(.0046)
Skill(2)			-.0018	-.0015
			(.0004)	(.0004)
Skill(3)x100			.0043	.0037
			(.0011)	(.0011)
Exp	.0815	.0586	.0652	.0670
	(.0082)	(.0058)	(.0073)	(.0077)
Exp(2)	-.0012	-.0010	-.0011	-.0010
	(.0002)	(.0002)	(.0002)	(.0002)
Exp(3)x100	.0012	.0009	.0010	.0008
	(.0002)	(.0003)	(.0003)	(.0003)

Table 13: Cumulative Returns to Firm, Industry and Skill Tenure: PSID

	Firm	Firm & Industry		Firm & Skill		Firm, Industry & Skill		
		Firm	Industry	Firm	Skill	Firm	Industry	Skill
1-digit								
2	.0351	.0186	.0348	.0213	.0403	.0113	.0280	.0266
	(.0089)	(.0098)	(.0063)	(.0093)	(.0078)	(.0098)	(.0067)	(.0083)
5	.0583	.0323	.0742	.0379	.0793	.0219	.0594	.0519
	(.0101)	(.0119)	(.0141)	(.0101)	(.0161)	(.0121)	(.0145)	(.0168)
10	.0925	.0526	.1077	.0641	.0998	.0418	.0853	.0659
	(.0140)	(.0173)	(.0224)	(.0152)	(.0240)	(.0174)	(.0227)	(.0246)
2-digit								
2	.0319	.0189	.0274	.0173	.0429	.0112	.0166	.0324
	(.0088)	(.0100)	(.0064)	(.0092)	(.0078)	(.0097)	(.0065)	(.0082)
5	.0553	.0341	.0576	.0337	.0846	.0237	.0344	.0626
	(.0100)	(.0128)	(.0141)	(.0108)	(.0161)	(.0124)	(.0140)	(.0167)
10	.0898	.0586	.0820	.0596	.1064	.0450	.0478	.0756
	(.0139)	(.0191)	(.0224)	(.0152)	(.0241)	(.0184)	(.0217)	(.0245)
3-digit								
2	.0316	.0222	.0210	.0183	.0413	.0158	.0091	.0352
	(.0087)	(.0100)	(.0065)	(.0092)	(.0078)	(.0101)	(.0067)	(.0081)
5	.0532	.0407	.0417	.0347	.0816	.0333	.0162	.0701
	(.0098)	(.0137)	(.0143)	(.0108)	(.0161)	(.0137)	(.0144)	(.0166)
10	.0850	.0718	.0509	.0606	.1028	.0632	.0136	.0911
	(.0137)	(.0211)	(.0225)	(.0152)	(.0240)	(.0211)	(.0222)	(.0245)

Notes: standard errors in parentheses.

APPENDIX

Table A1: Descriptive Statistics for the Regression Sample of Canadian Displaced Workers

	Occupation Switcher		Occupation Stayer	
	Industry	Industry	Industry	Industry
	Switcher	Stayer	Switcher	Stayer
Percentage Wage Difference				
Mean	-.0262	-.0335	-.0081	.0202
Standard Deviation	.4173	.4553	.2736	.2740
General Experience				
Mean	13.776	11.957	16.484	15.443
Standard Deviation	10.988	9.182	12.435	11.810
Firm Tenure				
Mean	3.273	3.763	3.630	4.481
Standard Deviation	4.894	4.367	4.869	6.186
Education				
Mean	10.679	10.656	10.701	10.911
Standard Deviation	3.023	2.657	3.605	3.067

Notes:
1. The percentage wage difference is the real post-displacement wage minus the real pre-displacement wage.
2. General experience is the number of potential years in the job market at the time of displacement calculated in the conventional way as: age - schooling years - 6.
3. Firm tenure is number of years with the same firm at the time of displacement.
4. Education is number of years of schooling calculated using mid-points from the education categories.

Table A2: Determinants of Changes in Log Wages for Displaced Male Workers: Canada

	Industry Stayer	Industry Switcher	Industry Switcher Occ Switcher	Industry Switcher Occ Stayer
Experience	-.0031	-.0114	-.0101	-.0083
	(.0066)	(.0053)	(.0063)	(.0086)
Experience^2 *100	.0059	.0154	.0096	.0151
	(.0151)	(.0116)	(.0140)	(.0017)
Tenure	-.0069	-.0140	-.0226	.0163
	(.0089)	(.0082)	(.0094)	(.0215)
Tenure^2 *100	.0303	.0046	.0289	-.0698
	(.0327)	(.0331)	(.0367)	(.1131)
R^2	.05	.09	.11	.21
N	278	517	425	92

Notes:
1. Standard errors in parentheses.
2. The specification also includes education, marital status, years since displacement, weeks without work after displacement and year of displacement, as in Neal (1995).

Table A3: Determinants of Changes in Log Wages for Displaced Male Workers: Canada

	Occ Stayer	Occ Switcher Industry Switcher	Occ Switcher Industry Stayer
Experience	.0034	-.0109	-.0101	-.0092
	(.0050)	(.0059)	(.0063)	(.0191)
Experience^2 *100	-.0094	.0078	.0096	-.0378
	(.0109)	(.0134)	(.0141)	(.0478)
Tenure	-.0027	-.0180	-.0226	.0093
	(.0070)	(.0087)	(.0094)	(.0286)
Tenure^2 *100	.0075	.0219	.0289	-.0019
	(.0263)	(.0347)	(.0367)	(.1323)
R^2	.05	.11	.11	.28
N	277	518	425	93

Notes:
1. Standard errors in parentheses.
2. The specification also includes education, marital status, years since displacement, weeks without work after displacement and year of displacement, as in Neal (1995).