Human Capital Specificity: Evidence from the Dictionary of Occupational Titles and Displaced Worker Surveys 1984-2000

by

Maxim Poletaev and Chris Robinson

Working Paper # 2008-3 **January 2008**

CIBC Working Paper Series

Department of Economics
Social Science Centre
The University of Western Ontario
London, Ontario, N6A 5C2
Canada

Human Capital Specificity: Evidence from the Dictionary of Occupational Titles and Displaced Worker Surveys 1984-2000*

Maxim Poletaev and Chris Robinson
Department of Economics, University of Western Ontario

January 11, 2008

*Chris Robinson is the CIBC Chair in Human Capital and Productivity, and Maxim Poletaev is a student in the PhD program, both at the University of Western Ontario. Their work is supported by the CIBC project in Human Capital and Productivity and by Human Resources Development Canada (HRDC). Funding for the project by the CIBC and HRDC is gratefully acknowledged. We would like to thank, without implicating, Audra Bowlus, Gueorgui Kambourov, Iourii Manovskii and Todd Stinebrickner for helpful discussions during this research.

Abstract

This paper uses information from the Dictionary of Occupational Titles (DOT) and Displaced Worker Surveys (DWS) to provide evidence on the source of human capital specificity. Measures of four basic skills are constructed from the detailed DOT information. These measures are used to characterize the skill portfolio of each job and to construct distance measures between jobs. The pattern of wage losses from the DWS shows that large losses are more closely associated with switching skill portfolios than switching industry or occupation code *per se* and that these switches represent large decreases in the underlying skill portfolio in the post-displacement job. The recent evidence for industry specific capital is re-examined. An analysis using the same methods as Neal (1995) that incorporates the skill portfolio measures provides further evidence in favor of broad skill based specificity.

1 Introduction

In the extensive literature that studies the determination of earnings and earnings inequality, human capital theory has played a central role.[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's (1964) initial discussion focussed on the dichotomy between firm specific and general capital. This distinction was important because while workers had a full incentive to invest optimally in general human capital, there were potential incentive problems in financing firm specific human capital. Subsequent authors also studied the implications for turnover.[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]

There is accumulating evidence that mobility has increased in the new economy.[4] Knowledge of the source of human capital specificity is increasingly important in an environment of increased mobility. The labor 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. The whole issue of the source of human capital specificity has been recently re-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 taken together, Neal (1995) and Parent (2000), provide evidence to suggest that industry specificity is much more important than firm specificity. If a large part of a country's human capital is industry specific, then some of the gain that would occur from the reallocation of workers in a flexible labor market from declining industries to growth industries would be offset by the destruction of industry specific human capital. Large

[1] Seminal works include Becker (1964), Ben Porath (1967), Mincer (1974). 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); Abowd, Kramarz, and Margolis (1999).

[4] See Kambourov and Manovskii (2004) for evidence for the United States.

industry specific investments would in fact tend to "lock in" labor to particular industries making adjustment difficult.

Kambourov and Manovskii (2002) argue that the evidence for industry specific capital is misleading and that specificity resides exclusively in occupational categories, with no role for either industry or firm. This work has been criticized by Pavan (2006), and the relative roles of industry and occupation remain unclear. In fact, while providing evidence for the importance of industry specific capital, Neal (1995), in the concluding section of his paper, leaves the question open. "I must acknowledge the possibility that results outlined above reflect the importance of skills that are not truly specific to given industries but rather specific to a set of jobs that are associated with the intersection of certain occupations and industries." He concludes that "[f]uture research in this area must confront the task of defining job categories that directly capture important skill specificities."[5]

In this paper we begin this task by developing a classification of "job categories" based on specific skill measures derived from the highly detailed job information provided in the Dictionary of Occupational Titles (DOT).[6] This information provides two distinct advantages over the use of industry or occupation codes for characterizing jobs. First, it is possible to associate a skill vector with each job so that jobs can be ranked and compared according to basic skill types and levels; second, the skill vectors can be used to construct measures of the closeness of jobs in terms of the underlying tasks and skill levels of the jobs. Thus, it is possible to evaluate a job change, say after displacement, in terms of how close the post- displacement job is to to the pre-displacement job in terms of the basic skill portfolio of the job. In addition, the magnitude of any movement in the skill portfolio, up or down, can be ranked. Does the new job use different skills? Does the new job use a lower level of the same skills?

The plan of the paper is as follows. In Section 2 we derive and discuss the basic skill portfolios associated with each job and the measures of distance between pre- and post-displacement jobs used in the analysis. In Section 3, we describe the relationship between switching industry or occupation code and switching skill portfolio in the Displaced Worker Survey (DWS) data for 1984-2000. Section

[5]Neal (1995), pp. 669-670.

[6]Ingram and Neumann (2006) developed a measures of skill using the Dictionary of Occupational Titles (DOT) and estimated returns to these skills. Our research on human capital specificity builds on this approach to defining basic skills.

4 examines the relation between the wage losses experienced following displacement and the different kinds of job changes in the DWS characterized by skill portfolio switching compared with industry or occupation code switching. The results show relatively large losses for job changes involving significant skill switching; industry codes and occupation codes appear to pick up some useful job information, but the results are generally strongest for the DOT based information. Moreover, the skill portfolio measures show that the displacements involving the large losses show substantial declines in the skill portfolio in the post-displacement job. In Section 5 we revisit the evidence for industry specific capital by incorporating the DOT based skill information in an analysis of specificity using the same basic methodology that Neal (1995) employed to provide evidence for industry specificity. The results show that while there remains some role for industry, the evidence supports a strong role for significant skill specificity using a measure based on the DOT information. They also show some evidence of a difference between narrowly specific *crystallized* skills that may be associated with industry, compared to more broader forms of human capital (*fluid* skills) that are more closely related to low dimensional skill portfolios. Section 6 presents some discussion and conclusions.

2 Basic Skill Portfolios and Distance Measures

It is important to establish the degree of specificity of human capital from a policy point of view given the evidence of increased mobility of workers in the new economy. What costs are associated with worker turnover in the form of loss of specific human capital?. What kinds of involuntary job switches can take place without major losses of specific human capital? Unfortunately it is difficult to derive firm conclusions on the source of human capital specificity from the evidence provided in the current literature. The main reason for this is the reliance on job histories as recorded in industry and/ or occupation codes. Neal (1995) points out that his results based on industry codes may not reflect true industry specific capital. Kambourov and Manowskii (2002) concludes with the finding that if occupational tenure is taken into account, there is little importance for industry specific capital in explaining wages in the PSID. 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."[7]

However, while occupation codes have the advantage over industry codes of being more closely related to tasks, they also have their own problems as a basis for defining specific capital. First, as a purely practical matter, they suffer from major coding consistency problems. In particular, using the PSID Retrospective Occupation-Industry Supplemental Data Files, Kambourov and Manowskii (2002) show that use of occupational code switches calculated from raw occupation codes will greatly over-estimate the amount of occupational mobility. Measures of occupation tenure are therefore subject to major measurement error.[8] Second, the occupation codes include a wide range of distinct occupations some of which use very different skills, say heavy lifting occupations versus manual 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 procedure for detecting human capital specificity at the industry or occupation level using displaced worker surveys relies on detecting relatively larger losses for industry or occupation switchers. There is no possibility of "progression" from a lower industry or occupation to a higher industry or occupation; all switches, given the investigator's chosen industry or occupation code aggregation level result in a loss of specific skill. There is no ranking of switches from one code to another: all are equivalent. Similarly, measuring industry or occupation specific capital from panel data relies on tenure in a particular industry or occupation; there is no possibility of an addition to that capital from tenure in a related or higher industry or occupation; all changes of industry or occupation stop

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

[8]The error arises primarily from the fact that the occupation coding from a respondent's description is done by a different coder each year. The retrospective data were constructed by using a single coder to retrospectively code all the raw responses of a single respondent. The retrospective codes showed dramatically fewer occupation switches.

the accumulation process. Skill specificity is unlikely to be as narrowly defined as the United States 3-digit occupations codes as studied in Kambourov and Manowskii (2002). 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 DOT provides a valuable, and relatively neglected, source of detailed information on over 12,000 jobs which can be used to distinguish between occupations that are similar and those that are different in the underlying tasks they perform. This allows all job changes, whether they involve switches in industry or occupation codes, to be distinguished by whether or not they involve very similar tasks and therefore should not involve significant changes in specific human capital.

2.1 The DOT Information

The data source is the final master file of the DOT, which contains information on 12741 unique DOT occupations or jobs.[9] This master file contains two forms of data on the characteristics of the occupation. First is the middle three digits of the DOT code itself which record the complexity of the interaction with "data", "people" and "things". Second, is the definition trailer which associates with each unique DOT code ratings on a large number of very detailed characteristics. One important set of characteristics come from the ratings on General Educational Development (GED) which is subdivided into three factors: reasoning development, mathematical development and language development. Each factor is then given a rating for each job, based on a detailed description of the rating. For example, for reasoning development, the definition of level 5 is:

Apply principles of logical or scientific thinking to define problems, collect data, establish facts, and draw valid conclusions. Interpret an extensive variety of technical instructions in mathematical or diagrammatic form. Deal with several abstract and concrete variables.

GED attempts to measure the general education or life experience necessary to perform a given

[9]This is version 4.3.

job in a satisfactory manner. By contrast, Specific Vocational Preparation (SVP) ratings measure the time required "to learn the techniques, develop the facility, and gain the knowledge for acceptable performance in a specific occupation." The time ratings vary from "short demonstration only" up to "over 10 years."

The remaining characteristics are divided into three groups: "Physical Demands and Environmental Conditions," "Temperaments," and "Aptitudes". The Physical Demands include a rating on the amount of strength needed, and an indicator of the presence of various requirements of the job, such as "climbing" or "stooping." Temperaments are defined as "personal traits" required by specific job-worker situations, such as "Performing effectively under stress." Finally, the Aptitudes factors use a 5 point scale to rate characteristics of the job such as "numerical ability", "form perception", "motor co-ordination", "finger dexterity", where the highest point on the scale is:

The top 10 percent of the population. This segment of the population possesses an extremely high degree of this aptitude

and the lowest point is:

The lowest 10 percent of the population. This segment of the population possesses a negligible degree of the aptitude

The DOT thus contains a very rich description of the characteristics of the DOT jobs. Ingram and Neumann (2006) used a factor analysis to extract a small number of basic factors ("skills") from this large amount of information on job characteristics and examined the pricing over time of these "skills." We follow Ingram and Neumann (2006) in using factor analysis to extract information from the DOT characteristics, but use the factor scores as the basis for ranking job changes according to some scale of underlying specific task changes.

2.2 Identification of the Underlying Skills

Each job in the DOT master file can be represented in the form of a vector of ratings on a large number of characteristics of the job. The basic rationale for using a factor analysis is the assumption that jobs can in fact be distinguished on the basis their requirements for (or use of) a relatively small number of skills ("factors"), such as fine motor skill, and that the relatively large number of characteristic ratings are reflections of these underlying skills. Formally, the model assumes that the L characteristic ratings for job j are generated by $K < L$ underlying skill factors according to the linear model:

$$\begin{aligned}
C_{1j} &= \mu_1 + \lambda_{11}\theta_{1j} + \lambda_{12}\theta_{2j} + ... + \lambda_{1K}\theta_{Kj} + \varepsilon_{1j} \\
C_{2j} &= \mu_2 + \lambda_{21}\theta_{1j} + \lambda_{22}\theta_{2j} + ... + \lambda_{1K}\theta_{Kj} + \varepsilon_{2j} \\
. &= \\
. &= \\
C_{Lj} &= \mu_L + \lambda_{L1}\theta_{1j} + \lambda_{L2}\theta_{2j} + ... + \lambda_{LK}\theta_{Kj} + \varepsilon_{Lj}
\end{aligned}$$

where C_{lj} is the rating for characteristic l on job j, θ_{kj} is the amount of underlying skill k used in job j and λ_{lk} is the factor (skill) loading of characteristic l on skill k. The scale of each factor, which is arbitrary, is usually set by imposing $\lambda_{11} = \lambda_{22} = ... = \lambda_{KK}$. The zero mean errors, ε_{lj}, are assumed to be uncorrelated with the factors, so that all the correlation among the characteristic ratings is explained by the common factors.

Each observation in the factor analysis is an $L \times 1$ vector of characteristic ratings for the observation, say job, j:

$$C_j = \mu + \Lambda\theta_j + \varepsilon_j$$

where C_j is an $L \times 1$ vector of the characteristics ratings for observation j, μ is an $L \times 1$ vector of means, θ_j is a $K \times 1$ vector of unobserved skill levels (factor scores) for observation j, Λ is an $L \times K$ matrix of the factor loadings and ε_j is an $L \times 1$ vector of errors for observation j. Given that θ and ε are uncorrelated:

$$cov(C) = E(C - \mu)(C - \mu)' = \Lambda\Sigma_\theta\Lambda' + \Sigma_\varepsilon$$

where Σ_θ is the covariance matrix of the factors and Σ_ε is a diagonal matrix of the so called *uniqueness* variances.

In general, the separate elements of Λ and Σ_θ are not identified. Further, the diagonal elements of Σ_ε and $\Lambda\Sigma_\theta\Lambda'$ are not separately identified. Identification is achieved in the standard factor analysis by normalizing the factors to be mean zero, with a standard deviation of one and by assuming that the factors are orthogonal, so that Σ_θ is diagonal. Factors are estimated sequentially, according to how much of the observed covariance in the characteristic ratings can be explained by the factor. The "first" factor is estimated so that it explains the maximum amount of covariance in the characteristic ratings; the second factor is estimated so that it explains the maximum amount of residual covariance that was not explained by the first factor, and so on. There are alternative ways of identifying the factors; for example, restrictions could be placed on Λ. This is appropriate in cases where the nature of the underlying factors is known and there is prior knowledge about which characteristic ratings could be considered measures of which factors.

In implementing this procedure, there are a number of choices to be made, for example, on how many characteristics to use and on the precise identification strategy. The details of our procedure are described in the Appendix. The DOT master file contains 12741 unique DOT occupations or jobs - many more than the three digit census occupation codes. The Displaced Worker Surveys use three digit census codes for industry and occupation. The DOT master file provides a corresponding census code for each DOT code. Factors are derived at the census code level from the average characteristic ratings of the DOT jobs that make up a census occupation. An important step is the weighting of the information so that the units of the derived factors represent standard deviations of the factors for the employed population. The factors derived in this analysis are based on the 1992 population of employees, representing the mid-point of the DWS data. As noted above, the factor analysis normalizes each factor to have a mean of zero and a standard deviation of one. Using employment weighted census occupations as the data for the factor analysis implies that a difference of one unit in a particular factor between one census occupation and another represents a move across the distribution of the factor scores in the employee population of one standard deviation. This is an important feature of the basic skill measure since it provides an interpretable distance measure between occupations.[10]

In extracting a small number of "factors" from a larger number of characteristics, factor analysis does not provide a unique solution without a number of specific assumptions relating to the factors. As noted above, a standard basic assumption is that the factors are orthogonal. To assess the robustness of the analysis in extracting factors that may be interpreted as "basic skills" the factor analysis was conducted under a range of specifications and a variety of rotations were employed.[11] In fact the factor analysis proved to identify a robust set of 3-4 factors in that variation in the specification or rotations produced similar factors in all cases. The factors identified by our analysis have similar characteristics to those of Ingram and Neumann (2006). The factor that explains most of the variance (about 40 percent) appears to capture some kind of general intelligence; the second factor (about 20 percent) emphasizes fine motor skills, while a third factor (about 12 percent) is more related to physical strength. After these three, the remaining factors contribute relatively little. One additional factor appears to pick up visual skills - the factor loadings emphasize color discrimination, color vision, far acuity, field of vision.[12]. The first two factors are very similar to the Ingram and Neumann factors that they call "intelligence" and "fine motor skills." Our third factor of physical strength is a combination of the Ingram and Neumann "physical strength" and "gross motor skills".[13]

2.3 Factor Scores: Occupation, Skill and Industry Switching

The output of the factor analysis is a vector of four factor scores for each 3-digit census occupation code. This is a representation of the 3-digit occupation in terms of a particular portfolio of underlying

[10]In previous work with industry or occupation, all switches between industries or occupations at a given coding level are the same, even though some may be "close" in the specific capital sense. The basic skill measure can be used to distinguish switches according to how different the skills are before and after the switch.

[11]Factor analysis produces an initial set of factors which are often subsequently "rotated" by the analyst to produce a set of "more interpretable" factors. The rotation procedure is usually described as an art of factor analysis. There is no correct procedure. In our analysis the original factors and all the rotations tried produced a similar pattern of results.

[12]After four factors the eigen values fall below 2, a common cut off point for significant factors. The analysis was restricted to these four factors that explain 77 percent of the covariance in the characteristic ratings.

[13]Ingram and Neumann (2006) identify the subdivision of the last two factors by imposing additional restrictions on the factor loading matrix. In our factor analysis, no additional restrictions were imposed. In fact the main results are insensitive to the "decomposition" of the remaining variance after the first two factors. Using a single third factor, or generating two more factors produces similar results in the distance measures.

basic skills. The 3-digit census codes provide the most detailed level of occupation changes in the DWS. Detailed occupation switching occurs after a displacement when there is a change in the 3 digit occupation code. Some of these switches may involve a greater "distance" between the pre- and post-displacement jobs in terms of the underlying skills used or tasks performed. Occupational coding levels provide one way of grouping the 3 digit occupations according to similarity. While staying in a 3 digit occupation after displacement implies staying in the grouped occupation, the 3-digit switchers may be subdivided into grouped occupation switchers and stayers. The factor score vectors, representing the portfolio of basic skills used on the pre- and post-displacement jobs, provide an alternative basis for calculating the "distance" between the jobs in terms of the underlying skills used or tasks performed. Staying in a 3-digit occupation implies staying in the same skill portfolio (same factor vector) since the factor vectors are constructed at the 3-digit occupation level. However, the factor score information can be used to provide an alternative subdivision of the 3-digit occupation switchers into skill switchers and skill stayers instead of into grouped occupation switchers and stayers.

Three aspects of these factor scores are used in the analysis to identify switchers and stayers in this subdivision. First is the order information: what is the "main" factor as defined by the factor with the highest score? What is the second factor, etc. Second is the level information: how important is the main factor as defined by the level of the main factor score? Third is the change information: how large is the change in the main factor score or other factor scores? This information can be thought of as three ways of constructing weights in a weighted euclidean distance measure for the factor score vectors.

Industry switchers are identified by those changing industry code. In this analysis we follow Neal (1995) in focussing on industry coding at a level that produces 33 pre-displacement industries for analysis with the displacement data.[14] Since industry and occupation codes are separate, all industry stayers could be occupation switchers and vice-versa. Similarly, there are no definitional constraints on the relation between industry and skill. However, in fact there is a correlation between industry and occupation, or industry and skill switching. This correlation between industry and occupation

[14]Neal excludes two pre-displacement industries, agriculture and construction, on the grounds that displacement is not clearly defined for seasonal workers.

switching has presented a serious problem for assessing the extent of industry or occupation specific capital in a situation in which the switches are measured with error.[15]

3 Industry, Occupation and Skill Switching in the DWS, 1984-2000

Table 1 describes the job changes by industry, occupation and skill change following plant closures. The data used for the analysis come from the DWS for 1984-2000. The selection criteria for the data are mostly the same as in Neal (1995) and are described in the Appendix.[16] The industry groups are those used in Neal (1995). Three levels of occupation groups are used: the 3-digit census codes, the census "detailed occupation group" codes and the census "major occupation group" codes. The detailed occupation group codes group the 500 3-digit occupations into 45 occupations; the major occupation group codes reduce this to 13 occupations. There is a large amount of switching across industry groups: 64.03 percent. There is also a large amount of switching across occupation groups. At the 3 digit level 67.80 percent switch occupation. This is reduced to 60.21 percent and 49.22 percent at the more aggregate occupation groupings, but even at the major group level with only 14 groups one half switch occupation. This would be a large amount of switching of basic skills if grouped occupation was a good proxy for basic skill portfolio.

Using the factor scores, based on the DOT information, a number of measures of basic skill switching were constructed. Using simply the order information, 39.59 percent change main skill; this still suggests a narrow definition of skills in that almost 40 percent are having to change skill on displacement. Using the level and distance information to construct alternative measures reduces the number of switchers substantially. Two representative measures are reported in Table 1. Skill Portfolio Change 1 (Skill PC1) denotes a skill change when the order information indicates a switch in the skill portfolio and this is confirmed by the distance and level information: the change in the score of the original main skill cannot be too small and the level cannot be too low. The magnitudes in this case are a change of no less than one half a standard deviation unit and a level of the original main skill no less that one half of a standard deviation unit above the mean. Similar numbers occur

[15]See Neal (1999) and Kambourov and Manovskii (2002) for some discussion of the measurement problems.

[16]The DWS is held every two years. Neal (1995) uses data for the 1984-1990 period. We extended this to additional surveys but did not go beyond 2000 due to the complications of a significant change in occupation codes in the following years.

with any variation on these criteria that are not too extreme. This reduces skill switching to below a quarter. It therefore permits an examination of the hypothesis that a large number of jobs are relatively close together in terms of the portfolio of skills used. Skill Portfolio Change 2 (Skill PD2) allows for the possibility that some of those classified as stayers by the order information should really be classified as switchers on distance grounds. Thus, the original classification to stayer on the basis of keeping the same main skill is reversed if there is a large change in the main skill factor score.[17] Skill PC2 results in 27.88 percent switchers - still interpretable as a definition based on the hypothesis of the availability of a large number of similar jobs in terms of their skill portfolio for displaced workers compared to what is implied by either the industry or occupation code switching patterns. Table 1 also shows that the patterns are very similar for males and females.

3.1 The Relation Between Occupation Code and Skill Portfolio Switching

From Table 1, occupation switching ranges from 67.80 percent to 49.22 percent, depending on the level of occupational coding. This is much higher than skill switching using the DOT based measures. All occupational stayers at the 3-digit level have to be skill stayers by definition. In this section the focus is on how the skill change measure partitions the occupation switchers. This is described in Table 2. Using the Skill PC1 measure, of the 4285 that switch 3 digit occupation, only about one third (1474) significantly change their skill portfolio. The fraction is slightly higher for males (36 percent) than for females (32 percent). Using the Skill PC2 measure this rises to about 40 percent, still leaving a majority of occupation switchers with no significant change in their skill portfolio. Again the pattern is similar for males and females. Aggregating up to the most aggregate occupation grouping, out of the 3111 that switch major occupation group only 1300, or 42 percent, significantly change skill by the Skill PC1 measure and only 48 percent by the Skill PC2 measure. If being able to find a job with a similar skill portfolio is more important for displaced workers than being able to find a job in the same occupation *per se*, then these proportions in Table 2 suggest

[17]The magnitude in this case is one standard deviation change to move a stayer based on order to a switcher. To keep the number of switchers relatively low, the criteria for confirming a switch among switchers based on the order information were slightly relaxed. The change value was 0.3 of a standard deviation and the level value was 0.6. As with Skill Change 1, similar numbers are produced with alternative magnitudes over a range of alternative values, provided they are not extreme.

that a substantial number of displaced workers who switch occupation could avoid serious wage loss. The evidence presented in section 4 below suggests that this is true.

3.2 The Correlation Between Industry, Occupation and Skill Portfolio Switching

The standard industry and occupation codes are designed independently, one based on the product produced and the other based on tasks performed. However, examination of the categories shows some clear overlap in the sense that some occupations have a close relationship to some industries - such as farmer and agriculture. The industry classification may in fact capture some aspects of the kinds of tasks carried out that are not fully captured by occupational classifications or skill measures that are based on them. The industry classifications are more product based: apparently similar tasks, according to the occupational classification or a skill portfolio measure, may be different when different products are involved. Thus, it is important to clarify the role played by the different types of information available in industry and occupation codes, as well as broader skill portfolio measures, to get a full picture of what kinds of jobs are similar. Table 2 showed that a large fraction of occupation switches are not significant skill portfolio switches. Table 3 shows the degree of overlap of skill and occupation switching with industry switching.

Table 3 shows a clear correlation between industry and occupation switching in that most observations in the sub-table blocks in Table 3 for industry and occupation are along the diagonal. The largest group in all cases is the group that switches both industry and occupation. For all workers this is over one half of the sample at the 3 digit occupation level. At the major group level this falls to just under 40 percent. By contrast, the skill measures result in the largest number of observations in the group that switches industry but does not switch skill. Within industry switchers, over 70 percent do not switch skill and within industry stayers, 86 percent do not switch skill, using Skill PC1. Almost all workers that stay in the same industry also stay with the same skill portfolio, producing an overlap in staying in skill and industry, so that there is some correlation between industry switching and skill switching. However, the correlation is low enough to investigate differences in skill and industry switching independently.

4 Wage Losses by Industry, Occupation and Skill Switching in the DWS, 1984-2000

Neal (1995) provided evidence from the DWS, 1984-90, in favor of the importance of industry specific capital. The evidence he presented was obtained through an indirect approach to identifying industry specific capital, in the sense that there was no direct measure of industry tenure used.[18] A direct approach would correspond to estimating Neal's equations (1)-(3):

$$w_1 = \alpha(experience) + \theta(industry - tenure) + \gamma(firm - tenure) + X\beta + \epsilon_1 \quad (1)$$

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

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

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. 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 $\theta(industry - tenure)$ 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.

The issue of larger losses for more experienced industry (or occupation, or skill) switchers is addressed in section 5, where the skill portfolio measures developed here are incorporated into Neal's analysis. In this section evidence is presented on the differences in the mean wage losses experienced by workers who either stayed or switched industry, occupation or skill. For the simple industry case, this is equivalent to estimating the average $\theta(industry - tenure)$ term. Since the focus in this paper is on identifying the availability of "similar" jobs to displaced workers, the main point of interest

[18] Industry tenure is not available in the DWS.

is how wage losses are associated with various combinations of switching or staying in industries, occupations or skill portfolios. As in Neal, the restricted sample of workers displaced through plant closings is assumed to approximate a sample of exogenous displacements.[19]

The mean log wage change in the displaced worker sample for 1984-2000 was -0.0911; for males the loss was -.1038, while for females it was -.0713. Table 4 shows that for industry, occupation and skill, each considered separately, the losses for switchers were greater than the losses for stayers. This holds for both unconditional mean losses and conditional mean losses, where the conditioning variables are schooling, experience, pre-displacement tenure, years since displacement and weeks without work after displacement. These are essentially the same variables as those used in Neal (1995).[20] In general the conditional and unconditional means are almost always very close, and the presentation and discussion of the results focuses on the conditional means. Industry switchers have a mean log wage loss that is about twice the magnitude of that for stayers: -.1108 compared to -.0560. This also holds true for occupation and skill portfolio. The magnitudes are quite similar for the industry and occupation groups; the skill portfolio magnitudes are a little higher.

4.1 Occupation and Skill Portfolios

Since Table 3 showed a degree of overlap between industry, occupation and skill portfolio switching it is not surprising that the wage loss patterns for industry, occupation and skill switch status considered separately are similar. The more interesting question is the relative importance of industry, occupation or skill status in producing these common results. The difference between the occupation and the skill portfolio results is primarily due to a subdivision of occupation switchers into skill portfolio switchers and stayers - in effect, reallocating some switchers into stayers. This reallocation results in the remaining switchers having a significantly higher mean loss while the enlarged group of stayers has a marginal increase in their loss. These relationships are explored in detail in Table 5. The conditional mean losses are estimated separately for each combination of occupation and

[19] While this is a common assumption, it is not entirely innocuous since bad plants may be more subject to closure, in the sense of plants with on average worse workers are first to be closed. In addition, there is usually some notice or expectation of plant closure which can also result in a selected sample of displaced workers.

[20] Other variables used in Neal (1995) were insignificant and had no effect on the estimated conditional means; these were dropped.

skill portfolio switch. The first four columns report the results for the overall sample; the remaining columns split the sample into males and females. The patterns are the same by sex.

For 3 digit occupation, by construction there is no cell for workers staying in the occupation and switching skill portfolio. For grouped occupations this cell does have observations, though the sample sizes are small, especially for the separate samples by sex. Reading across a row there is a clear and consistent pattern of increasing losses. That is, the lowest losses are for those who do not switch skill portfolio and the highest are for those that do. For major group occupation and the Skill PC1 measure, the smallest loss occurs for workers staying in both skill and occupation (-.0603); followed by those staying in skill, but switching occupation (-.0916); followed by those switching skill, but staying in the same occupation (-.1158). The highest loss (-.1588) occurs for those switching skill and occupation. The same pattern, with very similar magnitudes, occurs for Skill PC2. The skill measure thus clearly adds something beyond the occupation information, and the consistent ordering suggests a greater importance for the skill measure. Switching skill or not while staying in the same major occupation doubles the loss: -.0578 vs. -.1233 (-.0603 vs. -.1158 for the Skill PC1 measure.) By contrast, switching or staying in a major occupation group makes a much smaller difference, provided the worker does not switch skill: -.0578 vs. -.0870 for the Skill PC2 measure (-.0603 vs. -.0916 for the Skill PC1 measure).

The pattern is the same for both males and females, but the greater importance of the skill measure is particularly clear for the male sample. At the major occupation group level, switching skill appears to be almost all that matters. The losses are quite insensitive to switching occupation group within either skill switchers or skill stayers. For Skill PC1 stayers, switching major occupation results in a loss of -.0980, which is only a little higher than the loss from staying in the same major group of -.0759. For Skill PC1 switchers, switching major occupation results in a loss of -.1678 which is only a little higher than the loss from staying in the same major group of -.1450. The magnitudes are similar for the Skill PC2 measure.

While the particular job changes, even after a presumed exogenous displacement, are likely to be generated by a complex process, relatively low losses for workers that are able to find jobs that do not involve a significant change in their skill portfolio would suggest that the pre- and post-displacement jobs may be quite similar in terms of their underlying tasks and the level at which they are being performed. Moreover, the availability of jobs that are relatively close to one another suggested by the results for the skill measures stands in contrast to the availability suggested by occupation code switching. Even at the most aggregate occupation code level of major group, switching occupation occurs for half the displaced workers (at the 3 digit level it is over two thirds) compared to only a quarter making a significant change in skill portfolio.

4.2 Industry and Skill Portfolios

Table 3 showed a degree of overlap between industry and skill portfolio switching and Table 4 showed similar wage loss patterns for industry and skill switch status considered separately. Neal (1995) speculated that industry may be only one part of the story in characterizing similar jobs. Table 6 provides some evidence for assessing the relative importance of industry and skill status in producing these common results. Table 6 reports the conditional mean losses estimated separately for each combination of industry and skill portfolio switch. The first four columns report the results for the overall sample; the remaining columns split the sample into males and females. The results show a pattern of increasing losses across a row: the largest losses are for the workers that switch skill portfolio, and the smallest for those that do not. For the Skill PC1 measure, the smallest loss occurs for workers staying in both skill and industry (-.0471); followed by those staying in skill, but switching industry (-.0889); followed by those switching skill, but staying in the same industry (-.1098). The highest loss (-.1657) occurs for those switching skill and industry. The same pattern, with very similar magnitudes, occurs for Skill PC2. Within skill stayers or switchers, switching industry does increase the loss. This suggests that some aspect of the skill, that is not picked up by the DOT information, is product related. However, the difference made by switching skill portfolio is more important than that made by switching industry.

The overall mean industry switcher loss from Table 4 is -.1108. However, workers that stay in the industry but switch skill portfolio lose just as much: -.1098 for Skill PC1 and -.1100 for Skill PC2. By contrast, the overall (conditional) mean skill portfolio switcher loss from Table 4 is -.1534 (Skill PC1) or -.1500 (Skill PC2) and workers that stay in the skill portfolio but switch industry lose much less: -.0889 (Skill PC1) or -.0850 (Skill PC2). The industry stayers have a relatively low (conditional) mean loss from Table 4 of -.0532. However, Table 1 shows that about two thirds of all workers switch industry, and hence, this relatively low loss from staying in the same industry can only be achieved by one third of workers. By contrast three quarters of all workers, by staying in the same skill, avoid large losses. On average their losses are -.0725 or -.0695, which are quite close to the average losses of industry stayers.

4.3 Issues of Interpretation: Underlying Sources of Wage Loss

The results in Tables 4-6 show relatively low wage losses associated with staying close to the skill portfolio observed in the pre-displacement job. While displacements due to plant closings may be considered exogenous displacements, the skill distance changes are not, in general, exogenous. In any skill portfolio, for example, the "better" workers may have a higher probability of a small distance move. The results, therefore, do not show the wage differences that would occur for a worker randomly assigned to a new job skill portfolio. Rather, they show that using the distance measures employed in this paper, a relatively large group of workers are able to find new jobs that have skill portfolios that are close to their old ones and to experience relatively low wage losses. Thus the results should be interpreted as a description of the environment, in terms of job options (possible skill portfolio and wage outcomes), faced by a random sample of workers experiencing displacement. The description suggests that a relatively large fraction of them will end up experiencing small changes in both skill portfolio and wages.

A major advantage of characterizing pre- and post-displacement jobs by their skill vector rather than their industry or occupation codes is that the changes in the pre- and post-displacement jobs can be ranked in two dimensions. First, they can be ranked in terms of how close they are in terms of their skill portfolio using an interpretable distance measure based on the factor score changes. Second, the direction of change for each skill can be signed and the magnitudes ranked. By construction the mean of each skill from the factor analysis is zero and the standard deviation is one. Using the population of employees in 1992 as weights implies that a difference of one unit in a skill score is equivalent to moving one standard deviation in the population of employees. That is, starting with two workers at the same point in the distribution of a given skill among employees in 1992, if one worker had the skill increased by one unit, this would put them one standard deviation higher in that population. The first column of Table 7 shows the mean changes in the four basic skills between the pre- and post-displacement jobs for the sample of displaced workers. For the full sample, overall the average changes are typically negative and but small. For the first and second factors ("intelligence" and "fine motor skills" related, respectively) the changes are -.0397 and -.0139. There is a marginal increase in the third factor ("strength/gross motor skills" related). The fourth factor ("visual skills" related) shows a small decline of -.0384.

The remaining columns of Table 7 show the breakdown by skill portfolio switchers and stayers, using the two skill portfolio change criteria, Skill PC1 and Skill PC2. Using either measure of skill portfolio switching, the switchers show strong declines in the first three factors, while the stayers show modest increases. The fourth factor changes are similar across switchers and stayers. These dramatic differences in the changes in the levels of the factors in the skill portfolios shed further light on the pattern of wage losses among the displaced workers. The displaced workers with the large wage losses are those who switch skill portfolio, and this is correlated with switching industry or occupation. What the factor score changes also show is that these switches also involve moves to industry and occupation combinations where the levels of the skills are substantially lower. Given the units of the factor scores, the drop in the first two factor scores, for example, are a third of a standard deviation or more, in terms of the distribution of those factors in the 1992 employee population. Whatever the mechanism is for finding a post-displacement job, the big losers are those that end up in jobs with skill portfolios that are substantially lower in their factor (basic skill) scores.

5 Revisiting the Evidence for Industry Specific Human Capital

The evidence for industry specific human capital has taken two forms. The first is the indirect method of Neal (1995) which uses plant closures from DWS data to construct a sample of job displacements which are assumed to be exogenous, but which has no direct measure of industry tenure. The second is the direct method of Parent (2000) and Kambourov and Manovskii (2002) which uses all job changes in panel data and which employs a direct measure of industry tenure.

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. The direct approach to analyzing firm, industry or occupation specific human capital, as in Parent (2000) and Kambourov and Manovskii (2002), then typically add tenure with a firm and years of experience in the current industry or occupation to capture these types of human capital. Neal (1995) and Parent (2000) presents evidence for industry specific capital. Kambourov and Manovskii (2002) argue that the panel data evidence is more consistent with occupation specific capital. Pavan (2006) argues that there are serious endogeneity problems with the direct approach that are not solved by the standard IV techniques employed in the literature.

5.1 Industry and Skill Specificity: An Application of Neal's Indirect Method

The idea of a distance between basic skill portfolios, based on the DOT information, and defined in terms of a switch distance that results in around three quarters of displaced workers staying in their same basic skill shows that a large fraction of displaced workers appear to avoid large wage losses by regaining jobs with the same basic skill portfolio. This evidence on the differences in the conditional mean wage losses experienced by workers who either stayed or switched industry, occupation or skill is equivalent, for the simple industry case, to estimating the average $\theta(industry - tenure)$ or $\theta(occupation - tenure)$ or $\theta(skill - tenure)$. In terms of Neal's (1995) framework, for stayers the wage loss after displacement is less than the wage loss for switchers by $\theta(industry - tenure)$ 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 cannot test this hypothesis directly because of the absence of data on industry tenure in the DWS. Instead, he estimates the following equation separately for switchers and stayers:

$$\Delta lnw = \beta_0 + \beta_1 experience + \beta_2 experience^2 + \beta_3 tenure + \beta_4 tenure^2 + Z\zeta + \epsilon \tag{4}$$

where Δlnw is the change in the log wage between post- and pre-displacement jobs for a worker and the experience and tenure variables both refer to pre-displacement values. The vector Z is a set of controls.[21] 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 U.S. Displaced Worker Surveys (DWS) for the years 1984, 1986, 1988 and 1990 are the data sources used in Neal (1995). Neal 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 percent greater than the less experienced. If neither worker switched industry, the more experienced worker's losses are only 13 percent greater than those of the less experienced.[22]

In this section we report the results of re-estimating Neal's equation (4), subdividing his sample of industry switchers into those who also switched their skill portfolio.[23] If industry is the important source of specificity then the subdivided sample should yield similar results for the skill portfolio 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 portfolio should have greater relative losses for the more experienced workers than the industry switchers who did not switch skills. The results are presented in Table 8. Neal's original experiment compares the loss for 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

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

[22] Neal focuses on the results for 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.

[23] We are grateful to Derek Neal who provided us with his original code to make exact replication and extension of his analysis possible.

experience and 5 years of tenure. Table 8 reports the results evaluated at these values.[24]

The first row reports the results from the original Neal experiment on the extended data set. The results have the same pattern as the original experiment: the incremental wage losses for more experienced workers are larger for industry switchers (-.2305 vs. -.1449). The lower rows show that the same pattern occurs for skill. The incremental wage losses for more experienced workers are larger for skill switchers (-.2880 vs. -.1722 for Skill PC1, and -.2353 vs. -.1788 for Skill PC2). When the results are presented for the disaggregated groups, the incremental losses generally increase across the rows. That is, the incremental losses are largest for skill switchers and smallest for skill stayers. In fact, subdividing the skill switchers into industry switchers and stayers shows that industry switching status is unimportant given a skill switch. Subdividing the skill stayers, however, still shows a role for industry switching.

Neal subjected his basic OLS results to various robustness checks including modeling the selection into industry switcher or stayer status. The primary concern is that while the displacement may have been exogenous due to plant closing, the subsequent job obtained could be endogenous. Neal's selection model uses primarily the level and growth rate of the pre-displacement industry as the instruments in the selection model for industry switching. We calculated analogous instruments for skill.[25] Table 9 presents the selection corrected results for comparison with Table 8. Comparison of the tables shows that, as in Neal (1995), the results are robust to a simple form of selection correction.

Thus, if the type of analysis used in Neal (1995) to provide evidence of industry specific human capital is amended to incorporate basic skill measures, the results suggest a large role for basic skill specificity. The evidence for industry specificity is substantially reduced, but the results indicate that some aspects of the skills used or the tasks performed on a job that are not captured by occupation code based skill information is picked up by the industry code information. The magnitudes of the relative losses remain large. They are particularly large when comparing the relative losses of experienced workers that stay in both skill portfolio and industry to those that switch skill portfolio - up to an almost 20 log point difference. However, a particularly interesting feature is the asymmetry

[24]The pattern of results is similar at alternative evaluation points - see Poletaev and Robinson (2004)

[25]The construction of the instruments is described in detail in the Appendix.

in the disaggregated comparisons: while industry switching or staying appears to be largely irrelevant among the skill switchers, the skill stayers do appear to have a subset, indicated by switching industry status, that have lost a substantial amount of specific capital. For both the Skill PC1 and Skill PC2 measures, experienced workers that remain in, or close to, the same basic skill portfolio still have relative losses that are 10 percent higher if they switch industry. Apparently similar tasks, according to the occupational classification or a DOT-based skill portfolio measure, may be different when different products are involved.

The asymmetry in the effect of industry switching could be a reflection of a difference between *fluid* and *crystallized* skills. The psychology literature on intelligence introduced a distinction between *fluid* and *crystallized* intelligence.[26] There is a very large literature that explores this distinction in various contexts. A recent application of this kind of distinction to life skills including workplace skills, in connection with the International Adult Literacy Survey, is Murray, Clermont and Binkley (2005). In terms of specific human capital, crystallized skills could be thought of as more narrowly specific human capital, skill or knowledge, compared to fluid skills, which would have more broader application. Consider, for example, a worker with a basic skill portfolio that is consistent with the skills necessary to be a good sales person. The basic skill portfolio associated with being good as a sales worker could be carried across industries. However, the worker may also have specific human capital in the form of crystallized skills or knowledge connected to the product, or to buyers of the product, that would be lost if they switched industries and were involved in selling a different product to different customers. In this case, if the worker switched basic skill - i.e. was no longer working in sales, it would would not matter whether they also switched industry or not since the specific human capital in the form of crystallized skills or knowledge connected to the product, or to buyers of the product, would be lost in any case since the worker was no longer in sales. On the other hand, if the worker remains in sales it would make a difference if the worker switched industry or not. In particular, the crystallized specific capital would be lost if the worker switched industry.

[26]See, for example, Cattell (1971) for early work on this distinction.

5.2 Comparison with Evidence from Panel Data

Panel data has been used to provide evidence of industry specificity, using a direct measure of industry tenure. Using data from both the PSID and the NLSY, Parent (2000) takes a direct approach to identifying sources of specificity, similar to Neal's equations (1) - (3). Parent's basic statistical model is:

$$lnw_{ijkt} = \beta_0 OJ_{ijt} + \beta_1 T_{ijt} + \beta_2 Exp_{it} + \beta_3 Expind_{ikt} + \alpha_i + \theta_{ij} + \gamma_{ik} + \epsilon_{ijt} \tag{5}$$

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 experience, and $Expind$ is experience in the current industry. Parent adds the additional variable, OJ, equal to one if firm tenure is greater than one to allow for expected nonlinearities in the firm tenure effect. He also includes higher order polynomial terms in the experience and tenure variables as well as other "controls". 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 behavior.[27]

The direct approach used by Parent (2000) and Kambourov and Manovskii (2002) has been strongly criticized by Pavan (2006). Pavan (2006) specifies a search model in which career-specific and firm-specific matches determine job mobility and wage growth. He shows that the standard IV procedure used in the direct approach literature is inconsistent for his model. His monte carlo results show that the IV procedure does not solve the endogeneity problem and leads to spurious results. However, for comparison with the evidence from this branch of the specificity literature, in this section we report on the incorporation of skill measures into the direct approach.

The evidence on specificity from this approach, both with US and Canadian panel data sets was examined in Poletaev and Robinson (2004) using basic skill measures similar to those employed in this paper. In all cases of estimation technique and industry definition, and across both the NLSY

[27] Parent attempts to deal with these problems via an instrumental variables (IV) methodology. See Parent (2000) for exact details of the approach.

and PSID data sets, Parent shows that inclusion of industry experience variables greatly reduces the firm tenure effect which, in the IV estimates, becomes insignificantly different from zero. The industry tenure variables which are added to the equation (5) are always highly significant. Parent concludes that the significant results for firm tenure are spurious and result from the correlation between firm tenure and industry tenure. Poletaev and Robinson (2004) shows that this result is greatly modified by the inclusion of a basic skill tenure measure.

The PSID has also been analyzed by Kambourov and Manowskii (2002), using the same methodology, but also 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 for the period 1968-1980. This recoding dramatically reduced the number of switches especially for occupation. The results of Kambourov and Manowskii (2002) support Parent's conclusion of insignificant firm tenure effects but cast substantial doubt on the importance of industry tenure in favour of occupation tenure. Poletaev and Robinson (2004) incorporated a basic skill measure with the PSID data of Kambourov and Manowskii (2002). Skill tenure returns are always significant. They are reduced relative to when industry tenure is excluded, but the reductions are relatively modest. Industry tenure returns are insignificant at the 3-digit level and are generally reduced when skill tenure is included. The reduction is more dramatic than for skill. Finally, Poletaev and Robinson (2004) report evidence from a Canadian panel data set, the Survey of Labour and Income Dynamics (SLID).

Overall, the evidence from the direct approach for the importance of basic skill specific human capital is consistent with the results reported in this paper using DWS data. Estimating returns to specific capital using data with endogenous job changes is a difficult problem. However, the panel data evidence is consistent with the DWS data in showing the importance of including broad skill measures in the analysis.

6 Discussion and Conclusions

The human capital literature distinguishes between general and specific capital. A number of studies have provided evidence for various forms of specific capital. Initially the literature emphasized firm specific capital. More recently, it has been argued that previous findings of the importance of firm specific capital were due to the neglect of incorporating industry specific capital. It has also been argued that the findings of the importance of industry specific capital were due to the neglect of occupation specific capital. This literature has relied on the use of industry or occupation codes to define switches or to measure industry or occupation tenure. In this paper we exploited a rich source of additional information on the underlying skills used in a job from the DOT which allowed the construction of measures of basic skills that cut across particular industry/occupation code categories. The main theme of this paper is that human capital is not narrowly specific to industries or occupations, as defined by standard classifications. Rather, to the extent that it is not completely general, the evidence suggests that it is specific to a limited number of basic skills that can be used in a wide variety of contexts.

The major advantage of the DOT information is that jobs can be characterized by their skill vector rather than their industry or occupation codes. As a result, in analyzing DWS data, changes in the pre- and post-displacement jobs can be ranked in two dimensions that were not possible before. First, they can be ranked in terms of how close they are in terms of their skill portfolio using an interpretable distance measure based on the factor score changes. Second, the direction of change for each skill can be signed and the magnitudes ranked. Thus, the extent to which post-displacement jobs involve different basic skills, or different levels of the same basic skills, can be examined. Very high level of mobility have been documented across 3 digit occupation codes, but even at the one digit level the mobility remains high. The basic skill vectors provide a means of assessing the extent to which this is mobility across jobs that use different basic skills. Much of the mobility appears to be across quite similar jobs.

It is important to establish the degree of specificity of human capital from a policy point of view given the evidence of increased mobility of workers in the new economy. An interesting question for any country is the extent to which its human capital is more or less specific, and what costs are associated with the human capital loss that accompanies worker turnover. An efficiently functioning labor market is continuously reallocating labor across industries in response to changing demands for different industry outputs. To the extent that only a small amount of human capital is industry specific, these re-allocations could take place without any major destruction of human capital. The evidence from the DSW suggests that while broader (*fluid*) specific capital may be transferred across a wide variety of industries and occupations, a more narrowly specific (*crystallized*) form of human capital may be lost when workers switch industries.

Displaced workers experience a wage loss. The DWS sample used in this paper shows a real wage loss of about 9 percent for all displaced workers. A large majority of these workers were reallocated across standard occupation and industry codes. However, using skill portfolio distance measure based on the DOT information, many of these reallocations did not involve large changes in the skill portfolio between the pre- and post-displacement jobs. The average wage loss is very unevenly distributed across displaced workers. The workers with the largest losses are also those with a significant switch in their skill portfolio. In fact, using the skill portfolio change measures of Sections 3 and 4, only about one quarter of displaced workers experience a major change in their skill portfolio. However, they suffer particularly large wage losses of around 15 percent on average.

There are a variety of possible sources for the wage losses following displacement. If human capital is specific at the level of a small number of basic skills, then a substantial deviation in the skill portfolio mix between pre- and post-displacement jobs, would result in a loss of specific capital, and the patterns of wage losses are consistent with this. Conversely, many switches of industry or occupation codes are not significant skill portfolio switches and in these cases the wage losses are relatively low. Skill portfolio switching appears more important. However, examination of the levels in the skill portfolios before and after displacement shows that, on average, the portfolio switchers have substantial declines in the basic skill levels (factor scores). Thus, many of those that experience the worst wage losses are in post-displacement jobs that not only use a different skill mix, but also use a lower level of skills. Thus, the loss of specific capital following displacement could take two forms. First, different types of skills may be the main ones used on the new job compared to the old job, losing the specific capital in the old skills. Second, the skill portfolio in the new job may have similar proportions to the old job, but use less of the skills, and hence under-utilize some of the specific capital in the old skills.

Empirical research on skill based specificity is still in an 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 Kambourov and Manowskii (2002). 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. Moreover, the evidence in Section 4 suggests that, in terms of the associated wage losses, these 3 digit occupations can be more usefully grouped by skill portfolio measures than by more aggregate occupation groups. The skill portfolio distance measure is useful for grouping similar occupation codes, but there remains the problem of distinguishing groups of occupations that belong to a career path. This is not a major issue for analysis of displaced worker data where the job changes are considered involuntary displacements rather than voluntary career moves. However, it is an issue for an analysis of more general job mobility. The information on the levels of the basic factors in the skill portfolios associated with successive voluntary job changes may be very useful.

References

[1] John A. Abowd, Francis Kramarz, and David Margolis. High Wage Workers and High Wage Firms. *Econometrica*, 67:251–334, 1999.

[2] Katharine G. Abraham and Henry S. Farber. Job Duration, Seniority and Earnings. *American Economic Review*, 77:278–297, 1987.

[3] Joseph G. Altonji and Robert A. Shakotko. Do Wages Rise with Job Seniority? *Review of Economic Studies*, 54:437–459, 1987.

[4] Gary S. Becker. *Human Capital.* National Bureau of Economic Research, New York, 1964.

[5] Y. Ben-Porath. The production of Human Capital and the Lifecycle of Earnings. *Journal of Political Economy*, 75:352–365, 1967.

[6] R.B. Cattell. *Abilities: Their Structure, Growth, and Action.* Houghton-Mifflin, Boston, 1971.

[7] Beth Ingram and George Neumann. The Returns to Skill. *Labour Economics*, 13:35–59, 2006.

[8] Gueorgui Kambourov and Iourii Manovskii. Occupational Specificity of Human Capital. Working Paper, 2002.

[9] Gueorgui Kambourov and Iourii Manovskii. Rising Occupational and Industry Mobility in the United States: 1968-1993. Penn Institute for Economic Research Working Paper 04-012, 2004.

[10] Jacob Mincer. *Schooling, Experience and Earnings*. National Bureau of Economic Research, Columbia University Press, New York, 1974.

[11] T. Scott Murray, Yvan Clermont, and Marilyn Binkley. *International Adult Literacy Survey. Measuring Adult Literacy and Life Skills: New Frameworks for Assessment*. Statistics Canada, Ottawa, 2005. Catalogue no. 89-552-MIE,no.13.

[12] Derek Neal. Industry-Specific Human Capital: Evidence from Displaced Workers. *Journal of Labor Economics*, 13:653–677, 1995.

[13] Derek Neal. The Complexity of Job Mobility Among Young Men. *Journal of Labor Economics*, 17:237–261, 1999.

[14] Daniel Parent. Industry-Specific Capital and the Wage Profile: Evidence from the National Longitidinal Survey of Youth and the Panel Study of Income Dynamics. *Journal of Labor Economics*, 18:306–321, 2000.

[15] Ronni Pavan. Career Choice and Wage Growth. Working Paper, 2006.

[16] Maxim Poletaev and Chris Robinson. Human Capital Specificity: Direct and Indirect Evidence from Canadian and US Panels and Displaced Worker Surveys. CIBC Human Capital and Productivity Project Working Paper, 2004-2, University of Western Ontario, 2004.

[17] Robert Topel. Specific Capital, Mobility and Wages: Wages Rise with Job Seniority. *Journal of Political Economy*, 99:145–176, 1991.

[18] Donald O. Willis. The Employment Relationship: Job Attachment, Work Effort, and the Nature of Contracts. In Orley C. Ashenfelter and Richard Layard, editors, *Handbook of Labor Economics*. North Holland, 1986.

[19] Robert J. Willis. Wage Determinants: A Survey and Reinterpretation of Human Capital Earnings Functions. In Orley C. Ashenfelter and Richard Layard, editors, *Handbook of Labor Economics*. North Holland, 1986.

A Appendix

In this appendix we describe the data sources and the specification used in the factor analysis that produced the four basic skills. The final DOT master file (version 4.3) has 12741 unique DOT codes.[28] Each DOT job has characteristics associated with it. Three characteristics come from the fourth, fifth and sixth digits of the DOT code itself: the complexity of the interaction with data, people and things. This provides a numerical ranking of the complexity. All other characteristics are provided in separate fields in the DOT master file. One field is related to three complexity characteristics, indicating whether they are a significant part of the job, irrespective of the ranking. The combined information on the complexity data is used in two forms: first it is used as a straight ranking, without reference to the significance of the interaction in the job; second, if the interaction is insignificant, a value of zero is given to the variable, as the lowest value on an increasing numerical scale derived from the raw codes. The raw numerical rankings for the three GED characteristics were all used directly, and the SVP characteristics were converted into year equivalents. The information on the eleven "Temperaments" characteristics (e.g. "performing effectively under stress") simply indicates the presence of absence of the trait and was coded zero or one.

The "Physical Demands and Environmental Conditions" characteristics take two forms. All the characteristics, except "strength" and "noise" are divided into the following levels: Not Present (Activity or condition does not exist), Occasionally (Activity or condition exists up to 1/3 of the time), Frequently (Activity or condition exists from 1/3 to 2/3 of the time) and Constantly (Activity or condition exists 2/3 of the time or more.) These were converted into fractions of time. The "strength" and "noise" characteristics each have five point scales: from "sedentary" to "very heavy" for strength; from "very quiet" to "very loud" for noise. Finally, the "Aptitude" characteristics were rated on a 5 point scale according to the fraction of the population possessing it at particular levels as described in the text.

The maximum number of characteristics for use in the factor analysis is 63: complexity (3), GED (3), SVP (1), Aptitude (11), Temperament (11), Physical (20), Environmental (14). Five subsets of these variables were tried in separate factor analyses. Following the standard factor

[28] There were 14 DOT code values that had "XXX" as the last three digits which were dropped.

analysis, two popular rotations were applied to the factors. The specification used in the paper excludes the environmental variables, as having the least to do with skill measures. Otherwise, all the characteristics are included and the basic, non-rotated form of the factors are used in the analysis.[29] In all specifications at least three factors are significant by normal factor analysis criteria, while a fourth is usually significant. The factor loadings were also quite stable across the alternative specifications.

The occupation codes in the Displaced Worker Surveys (DWS) are three digit census codes. The DOT master file contains 1990 census codes equivalent to the DOT codes. There are many more DOT codes than three digit census codes. For census codes with more than one DOT code, the average value of the characteristic across the DOT codes was assigned to the census code. There are some 1990 census 3 digit occupation codes that do not have a DOT equivalent. In total there are 500 1990 census 3 digit occupation codes. However, a small number of mainly teaching related occupations do not appear in the DOT, leaving 467 potential unweighted observations for the factor analysis. The actual data used for the factor analysis was a weighted sample of these 467 census occupations, where the weights were the employment weights by occupation for 1992 constructed from the March Current Population Survey (CPS) files - the mid-point of the 1984-2000 DWS data that were used in the analysis.[30] By construction the estimated factors have mean zero and a standard deviation of one so that using the employment weight produces factors that are interpretable in terms of their distribution in the population of employees.

The DWS data used in the analysis is for years 1984-2000. In these years it was relatively easy to convert the relevant census industry and occupation codes to the census 1990 coding available in the 4.3 version of the master file in the DOT. The restrictions on the data set almost the same as in Neal (1995). Age is restricted to less than or equal to 61. The pre- and post-displacement jobs are both full time. Class of worker is private sector employee; self employed are excluded. Observations with industry coded as agriculture or construction are excluded. Valid codes are required for industry and

[29] There are some cautions in the DOT manual regarding the use of the complexity variables across a wide range of occupations; accordingly specifications were tried with and without these variables. The results were largely insensitive to this variation.

[30] There were relatively small changes between the 1980 and 1990 census occupation codes, so that it is relatively easy to use consistent 1990 census coding for the 1984-2000 period. After 2000 there was a major change in occupation coding which made an equivalence for later data difficult.

occupation in both pre- and post-displacement jobs. Earnings less than 40 dollars in the past year are excluded. One additional restriction not in Neal (1995) is that a small number of observations with top coded earnings on either the pre-displacement or post-displacement job were excluded.

In the selection corrected version of his analysis of industry specific capital, Neal (1995) used the employment level and change in the industry at the time of displacement as instruments for whether the individual switches industry. Analogous instruments were constructed for skill switching by computing employment levels and changes in the four factors derived from occupational employment in the March CPS files. These are the instruments used in the selection corrected results in Table 9.

Table 1
Displacement Switching Patterns by Industry, Occupation and Skill

	All Workers		Males		Females	
	Switch	**Stay**	**Switch**	**Stay**	**Switch**	**Stay**
Industry	4047	2273	2436	1404	1611	869
	64.03%		63.44%		64.96%	
Occupation	4285	2035	2553	1287	1732	748
	67.80%		66.48%		69.84%	
Occupation (45)	3805	2515	2291	1549	1514	966
	60.21%		59.66%		61.05%	
Occupation (13)	3111	3209	1939	1901	1172	1308
	49.22%		50.49%		47.26%	
Main Skill (Order)	2502	3818	1496	2344	1006	1474
	39.59%		38.96%		40.56%	
Skill PC1	1474	4846	921	2919	553	1927
	23.32%		23.98%		22.30%	
Skill PC2	1762	4558	1077	2763	685	1795
	27.88%		28.05%		27.62%	

Table 2
Occupation and Skill Portfolio Changes

	Skill PC1		**Skill PC2**	
	Switch	Stay	Switch	Stay
Occupation				
Switch	1474	2811	1762	2523
Stay	0	2035	0	2035
Occupation (45)				
Switch	1416	2389	1673	2132
Stay	58	2457	89	2426
Occupation (13)				
Switch	1300	1811	1496	1615
Stay	174	3035	266	2943
	Males			
Occupation				
Switch	921	1632	1077	1476
Stay	0	1287	0	1287
Occupation (45)				
Switch	890	1401	1033	1258
Stay	31	1518	44	1505
Occupation (13)				
Switch	840	1099	943	996
Stay	81	1820	134	1767
	Females			
Occupation				
Switch	553	1179	685	1047
Stay	0	748	0	748
Occupation (45)				
Switch	526	988	640	874
Stay	27	939	45	921
Occupation (13)				
Switch	460	712	553	619
Stay	93	1215	132	1176

Table 3

Occupation and Skill Portfolio Switchers by Industry Status

	Industry					
	All Workers		**Males**		**Females**	
	Switch	Stay	Switch	Stay	Switch	Stay
Occupation						
Switch	3285	1000	1956	597	1329	404
Stay	762	1273	480	807	282	466
Occupation (45)						
Switch	2970	835	1795	496	1175	339
Stay	1077	1438	641	908	436	530
Occupation (13)						
Switch	2443	668	1520	419	923	249
Stay	1604	1605	916	985	688	620
Skill PC1						
Switch	1161	313	717	204	444	109
Stay	2886	1960	1719	1200	1167	760
Skill PC2						
Switch	1357	405	836	241	521	164
Stay	2690	1868	1600	1163	1090	705

Table 4

Mean Log Wage Losses for Industry, Occupation and Skill Portfolio Switchers and Stayers

	All Workers				Males		Females	
	Unconditional		Conditional		Conditional		Conditional	
	Switch	Stay	Switch	Stay	Switch	Stay	Switch	Stay
Industry	-.1123	-.0532	-.1108	-.0560	-.1272	-.0632	-.0859	-.0442
	(.0071)	(.0079)	(.0065)	(.0087)	(.0084)	(.0112)	(.0101)	(.0138)
Occupation	-.1113	-.0485	-.1108	-.0495	-.1233	-.0652	-.0921	-.0233
	(.0069)	(.0080)	(.0063)	(.0092)	(.0083)	(.0117)	(.0097)	(.0149)
Occupation (45)	-.1170	-.0518	-.1164	-.0528	-.1312	-.0633	-.0935	-.0366
	(.0074)	(.0074)	(.0067)	(.0083)	(.0087)	(.0106)	(.0104)	(.0131)
Occupation (13)	-.1223	-.0608	-.1196	-.0633	-.1283	-.0788	-.1053	-.0409
	(.0084)	(.0068)	(.0074)	(.0073)	(.0095)	(.0096)	(.0118)	(.0112)
Skill PC1	-.1521	-.0725	-.1534	-.0721	-.1656	-.0843	-.1303	-.0544
	(.0120)	(.0060)	(.0107)	(.0059)	(.0137)	(.0077)	(.0172)	(.0092)
Skill PC2	-.1467	-.0695	-.1500	-.0683	-.1670	-.0792	-.1206	-.0525
	(.0111)	(.0061)	(.0098)	(.0061)	(.0127)	(.0079)	(.0154)	(.0095)

Notes: Standard errors in parentheses. The conditioning variables are schooling, experience, pre-displacement tenure, years since displacement and weeks without work after displacement.

Table 5
Mean Log Wage Losses by Occupation and Skill Portfolio Switchers and Stayer Status

	All Workers				Males				Females			
	Skill PC1 Stay		**Skill PC1 Switch**		**Skill PC1 Stay**		**Skill PC1 Switch**		**Skill PC1 Stay**		**Skill PC1 Switch**	
	Occup Stay	Occup Switch	Occup Stay	Occup Switch	Occup Stay	Occup Switch	Occup Stay	Occup Switch	Occup Stay	Occup Switch	Occup Stay	Occup Switch
Occupation	-.0494	-.0883	-	-.1538	-.0651	-.0993	-	-.1659	-.0233	-.0739	-	-.1307
	(.0092)	(.0078)		(.0107)	(.0117)	(.0103)		(.0137)	(.0149)	(.0118)		(.0172)
Occupation (45)	-.0507	-.0939	-.1382	-.1545	-.0618	-.1085	-.1388	-.1670	-.0336	-.0739	-.1370	-.1303
	(.0084)	(.0084)	(.0539)	(.0109)	(.0107)	(.0111)	(.0744)	(.0139)	(.0132)	(.0129)	(.0775)	(.0176)
Occupation (13)	-.0603	-.0916	-.1158	-.1588	-.0759	-.0980	-.1450	-.1678	-.0372	-.0835	-.0889	-1391
	(.0075)	(.0097)	(.0311)	(.0114)	(.0098)	(.0126)	(.0461)	(.0144)	(.0116)	(.0152)	(.0418)	(.0188)
	Skill PC2 Stay		**Skill PC2 Switch**		**Skill PC2 Stay**		**Skill PC2 Switch**		**Skill PC2 Stay**		**Skill PC2 Switch**	
	Occup Stay	Occup Switch	Occup Stay	Occup Switch	Occup Stay	Occup Switch	Occup Stay	Occup Switch	Occup Stay	Occup Switch	Occup Stay	Occup Switch
Occupation	-.0493	-.0833	-	-.1503	-.0649	-.0914	-	-.1672	-.0233	-.0732	-	-.1209
	(.0092)	(.0082)		(.0098)	(.0117)	(.0108)		(.0127)	(.0149)	(.0125)		(.0154)
Occupation (45)	-.0511	-.0875	-.0951	-.1533	-.0624	-.0990	-.0918	-.1705	-.0337	-.0721	-.0942	-.1227
	(.0084)	(.0089)	(.0435)	(.0101)	(.0108)	(.0117)	(.0624)	(.0130)	(.0134)	(.0137)	(.0600)	(.0160)
Occupation (13)	-.0578	-.0870	-1233	-.1550	-.0737	-.0887	-.1447	-.1703	-.0342	-.0871	-.1001	-.1259
	(.0076)	(.0103)	(.0252)	(.0106)	(.0099)	(.0132)	(.0358)	(.0136)	(.0118)	(.0163)	(.0351)	(.0172)

Notes: Standard errors in parentheses.

Table 6

Mean Log Wage Losses by Industry and Skill Portfolio Switchers and Stayer Status

All Workers				Males				Females			
Skill PC1 Stay		**Skill PC1 Switch**		**Skill PC1 Stay**		**Skill PC1 Switch**		**Skill PC1 Stay**		**Skill PC1 Switch**	
Industry Stay	Industry Switch	Industry Stay	Industry Switch	Industry Stay	Industry Switch	Industry Stay	Industry Switch	Industry Stay	Industry Switch	Industry Stay	Industry Switch
-.0471	-.0889	-.1098	-.1657	-.0558	-.1041	-.1059	-.1831	-.0337	-.0677	-.1158	-.1343
(.0093)	(.0077)	(.0232)	(.0121)	(.0121)	(.0100)	(.0290)	(.0155)	(.0147)	(.0118)	(.0386)	(.0192)
Skill PC2 Stay		**Skill PC2 Switch**		**Skill PC2 Stay**		**Skill PC2 Switch**		**Skill PC2 Stay**		**Skill PC2 Switch**	
Industry Stay	Industry Switch	Industry Stay	Industry Switch	Industry Stay	Industry Switch	Industry Stay	Industry Switch	Industry Stay	Industry Switch	Industry Stay	Industry Switch
-.0438	-.0850	-.1100	-.1624	-.0516	-.0990	-.1171	-.1818	-.0315	-.0659	-.0973	-.1283
(.0096)	(.0079)	(.0204)	(.0112)	(.0122)	(.0104)	(.0267)	(.0144)	(.0153)	(.0122)	(.0315)	(.0177)

Notes: Standard errors in parentheses.

Table 7

Difference in Skill Portfolio (Factor Scores) Between Pre- and Post-displacement Jobs

FACTOR	All Displaced Workers	Skill PC1		Skill PC2	
		Switcher	Stayer	Switcher	Stayer
First Factor (General Intelligence Related)	-.0397	-.3821	.0645	-.3145	.0666
Second Factor (Fine Motor Skills Related)	-.0139	-.5057	.1357	-.3687	.1233
Third Factor (Strength and Gross Motor Skills Related)	.0400	-.2919	.1410	-.1643	.1190
Fourth Factor (Visual Skills Related)	-.0384	-.0215	-.0436	.0348	.0668

Table 8
Incremental Wage Losses for More Experienced Workers

<table>
<tr><th colspan="2">Industry Stayer</th><th colspan="2">Industry Switcher</th></tr>
<tr><td colspan="2">-.1449</td><td colspan="2">-.2305</td></tr>
<tr><td colspan="2">(.0340)</td><td colspan="2">(.0288)</td></tr>
<tr><th colspan="2">Skill PC1 Stayer</th><th colspan="2">Skill PC1 Switcher</th></tr>
<tr><td colspan="2">-.1722</td><td colspan="2">-.2880</td></tr>
<tr><td colspan="2">(.0250)</td><td colspan="2">(.0480)</td></tr>
<tr><td>Industry Stayer</td><td>Industry Switcher</td><td>Industry Stayer</td><td>Industry Switcher</td></tr>
<tr><td>-.1244</td><td>-.2004</td><td>-.2548</td><td>-.3016</td></tr>
<tr><td>(.0371)</td><td>(.0337)</td><td>(.0929)</td><td>(.0567)</td></tr>
<tr><th colspan="2">Skill PC2 Stayer</th><th colspan="2">Skill PC2 Switcher</th></tr>
<tr><td colspan="2">-.1788</td><td colspan="2">-.2353</td></tr>
<tr><td colspan="2">(.0252)</td><td colspan="2">(.0458)</td></tr>
<tr><td>Industry Stayer</td><td>Industry Switcher</td><td>Industry Stayer</td><td>Industry Switcher</td></tr>
<tr><td>-.1273</td><td>-.2104</td><td>-.2521</td><td>-.2453</td></tr>
<tr><td>(.0384)</td><td>(.0395)</td><td>(.0733)</td><td>(.0549)</td></tr>
</table>

Notes: Standard errors in parentheses.

Table 9
Incremental Wage Losses for More Experienced Switchers (Selection Corrected)

<table>
<tr><td colspan="2">Industry Stayer</td><td colspan="2">Industry Switcher</td></tr>
<tr><td colspan="2">-.1351</td><td colspan="2">-.2444</td></tr>
<tr><td colspan="2">(.0345)</td><td colspan="2">(.0301)</td></tr>
<tr><td colspan="2">Skill PC1 Stayer</td><td colspan="2">Skill PC1 Switcher</td></tr>
<tr><td colspan="2">-.1754</td><td colspan="2">-.2881</td></tr>
<tr><td colspan="2">(.0250)</td><td colspan="2">(.0471)</td></tr>
<tr><td>Industry Stayer</td><td>Industry Switcher</td><td>Industry Stayer</td><td>Industry Switcher</td></tr>
<tr><td>-.1161</td><td>-.2095</td><td>-.2541</td><td>-.3017</td></tr>
<tr><td>(.0373)</td><td>(.0342)</td><td>(.0842)</td><td>(.0552)</td></tr>
<tr><td colspan="2">Skill PC2 Stayer</td><td colspan="2">Skill PC2 Switcher</td></tr>
<tr><td colspan="2">-.1799</td><td colspan="2">-.2345</td></tr>
<tr><td colspan="2">(.0251)</td><td colspan="2">(.0453)</td></tr>
<tr><td>Industry Stayer</td><td>Industry Switcher</td><td>Industry Stayer</td><td>Industry Switcher</td></tr>
<tr><td>-.1204</td><td>-.2151</td><td>-.2427</td><td>-.2473</td></tr>
<tr><td>(.0384)</td><td>(.0338)</td><td>(.0753)</td><td>(.0539)</td></tr>
</table>

Notes: Standard errors in parentheses.