OCCUPATIONAL HUMAN CAPITAL: ITS ROLE AND IMPLICATION FOR EARNINGS

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ABSTRACT

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This dissertation research examines the role of occupational human capital in the determination of workers' wages and earnings losses following job displacement. In it, I explain the important role of occupational skills transferability in the labor market. The first chapter develops and estimates the measure of skills transferability applying two approaches. The first approach is based on Shaw's (1984) method, and the second one is based on Ormiston's (2006) method. The main difference between Shaw's (1984) and Ormiston's (2006) approaches is that Shaw's (1984) transferability matrix is a market-based approach, which reflects market as well as technical conditions. In particular, Shaw (1984) estimates skills transferability by examining an actual occupational change, arguing that there will be greater occupational mobility between jobs that have greater rates of skills transferability. On the other hand, Ormiston's (2006) skills transferability is estimated based on the knowledge, skills, and abilities (KSAs) shared across occupations. The accuracy of this estimate will be important for the subsequent two chapters, in which I examine the determinants of workers' wages over the lifecycle and earnings losses due to job displacement.

The second chapter studies the effect of occupational human capital on the workers' wages. Unlike previous studies that apply *occupational tenure* as a proxy for occupational human capital, this chapter applies the concept of Shaw's (1984) occupational human capital to capture the transferability of occupational skills and estimates a new measure of occupational human capital, so-called *occupational investment*. Using the National Longitudinal Survey of

Youth (NLSY) from 1979 to 2000, the key findings of this chapter suggest that occupational skills from previous jobs can also affect workers' wages at the current job and that *occupational investment* is one of the important sources of wages supporting Shaw's original work on wage determination. Specifically, five years of (3-digit) occupational investment relative to the current occupational tenure could lead to a wage increase of 7 to 16 percent. I also find that the general labor market experience accounts for a large share of workers' wages.

The third chapter investigates the role of occupational human capital in explaining variations in earnings losses following job displacement. Unlike previous studies on job displacement, this chapter uses a continuous measure of occupational skills transferability, developed in Chapter 1, to measure the similarity between the pre- and post-displacement occupations of reemployed displaced workers. Using the 2004, 2006, 2008, and 2010 Displaced Worker Survey (DWS), the main finding is that post-displacement earnings losses are highly correlated with the degree of similarity between pre- and post-displacement occupations. Displaced workers who find jobs in occupations similar to their previous jobs suffer smaller earnings losses than those who find less similar occupations. This relationship is non-linear in that higher skills transferability reduces the earnings losses at a decreasing rate.

Overall, this dissertation examines the measurement and outcomes of occupational human capital to support the idea that occupational skills are transferable across occupations and that skills transferability can help to explain workers' wages over the lifecycle and earnings losses associated with job displacement.

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THE ESTIMATION OF OCCUPATIONAL SKILLS TRANSFERABILITY

1. Introduction

The idea of occupational human capital has become particularly important in recent literature to understanding wage growth over the lifecycle and the distribution of earnings across the labor force (for example, Sullivan, 2006; Kambourov and Manovskii, 2009). With few exceptions, important contributions from most previous research have focused on the role of occupation-specific skills (i.e., skills that would be lost or not be applicable whenever workers change occupations) and neglected the idea that skills could be transferred across occupations. Ignoring this aspect of occupational human capital might introduce measurement error in estimation.

Most recent studies on the relationship between occupation-specific skills and wages use *occupational tenure*, the numbers of year spent in one particular occupation, as a proxy for occupational human capital (for example, Sullivan, 2006; Zangelidis, 2007; Kambourov and Manovskii, 2009). Presumably, the amount of occupational skills increases with tenure in the occupation and would not applicable whenever workers change occupations. These studies generally found the positive and significant effect of occupational tenure on individuals' wages. For example, using data from the PSID Retrospective Occupation-Industry Supplemental Data Files (Retrospective files) from 1968-1993 period, Kambourov and Manovskii (2009) find 5 additional years of occupational tenure increase wages by 12 to 20 percent, all else being equal.

However, occupational tenure measure may be an inadequate proxy for occupational human capital because whenever workers change occupations, the tenure measure is reset to zero, which implies that all the skills from the previous occupations would be lost. Yet it is likely that at least some portion of skills is transferred across occupations. For example, an engineer should be able to transfer some engineering skills to a clerical job. Arguably, including actual years of work experience in the wage equation will capture some of this transferability, but this measure does not vary by occupation and therefore cannot capture variation in the transferability of skills across occupations.

From a purely econometric standpoint, the occupational tenure measure assumes that all the skills from the previous occupations fall into the error term of wage equation. The occupational tenure variable will be endogenous if it is correlated with the omitted occupational skills transferability from the previous job that also affects wages. For example, if workers who have higher skills transferability from the previous job tend to stay in the current occupation longer to accumulate more specialized occupational skills and receive higher wage returns than their counterparts who have less skills transferability, then the estimate of return to occupational tenure would be (upwardly) biased and inconsistent.

In this chapter, I address the concerns raised here by developing estimates of occupational skills transferability, and in subsequent chapters I test the importance of this measure for estimating wage determination and earnings losses following job displacement. To measure occupational skills transferability, I apply two different measurement approaches. The first approach is based on Shaw's (1984) method, and the second one is based on Ormiston's (2006) method. Shaw's (1984) skills transferability is a market-based approach, based on an actual occupational change while Ormiston's (2006) skills transferability is a pure technical measure based on the knowledge, skills, and abilities (KSAs) shared across occupations.

To estimate Shaw's (1984) skills transferability, I use the March Current Population Survey (CPS), which is a large cross-sectional dataset of over 60,000 households. For

Ormiston’s (2006) skills transferability, I use the O*NET dataset to compute the ratio of shared 120 standardized knowledge, skill, and ability categories (KSAs) across occupations. The accuracy of skills transferability will be important for subsequent chapters (Chapters 2 and 3), in which I examine the determinants of workers’ wages over the lifecycle and the earnings losses of displaced workers. Despite the differences in the estimation methods, the estimated correlation between Shaw’s and Ormiston’s skills transferability is around 0.45, indicating a positive and modestly strong correlation.

Better estimates of skills transferability could lead to a further understanding of wage inequality (e.g., gender wage gap, or racial wage disparities). Specifically, in the gender wage gap literature, the male wage premium might exist because of the lower relative occupational mobility or higher skills transferability across occupations more commonly held by men, which in turn will contribute to higher wages. The skills transferability measure could also lead to a better estimate of earnings losses following job displacement. Displaced workers who find more similar occupations with higher skills transferability might suffer smaller earnings losses than those who find less similar occupations. From a policy perspective, the skills transferability measure can be used to estimate the costs of human capital destruction involved in structural change in economy.

This chapter is structured as follows. In Section 2, I explain the estimations of occupational skills transferability applying Shaw’s (1984) and Ormiston’s (2006) approaches. Section 3 discusses the strengths and weaknesses of each approach. Section 4 presents the estimation results, and the last section concludes.

2. The Estimation of Occupational Skills Transferability

This section describes two estimation methods of occupational skills transferability. The first method is based on Shaw's (1984) approach, and the second one is based on Ormiston's (2006) approach. The main difference between Shaw's and Ormiston's approach is that Shaw's occupational skills transferability is a market-based approach. In particular, Shaw (1984) estimates skills transferability by examining actual occupational mobility patterns and arguing that there will be greater occupational mobility between jobs that have a higher rate of skills transferability. On the other hand, Ormiston's occupational skills transferability is a technical approach based on a measure of commonality of knowledge skills and abilities (KSAs) across occupations. Each approach has strengths and weaknesses which I will discuss below. Therefore, these two methods of estimating measures of occupational skills transferability will be used and tested in the following chapters.

2.1 Shaw's Skills Transferability Method (Occupational Distance)

Shaw (1984) is the first one who recognizes the importance of transferability of occupational human capital in establishing particular labor market outcomes. Particularly, Shaw notes that the return to the stock of human capital from the former occupation is not completely foregone upon an occupational switch. Instead, the return to one's human capital stock depends on the degree of transferability of skills from one occupation to the next. She hypothesizes skills acquired in a particular occupation are portable across firms making them "occupation specific", rather than "firm specific". Unlike the case of general human capital, individuals would be able to transfer only a certain amount of their occupation-specific human capital stock in the event of an occupational change, and that amount inherently depends on the degree of "transferability" between the two occupations (Shaw, 1984).

Shaw (1984) estimates the transferability of skills using observed occupational changes. She proposes the probability of a change from one occupation to another is increasing in the transferability of skills between the two occupations. The greater the transferability is, the greater the incentive to change occupation and vice versa. This implies that the measure of the probability of occupational switch, P^{ij}, is closely correlated with the transferability of skills, γ^{ij}. However, the difficulty of directly using P^{ij} as the approximation of skills transferability is that it is likely to pick up the short-run causes and the determinants of mobility that are unrelated to skills transferability. Instead, she proposes an alternative measurement of transferability which assesses occupational movement more closely than P^{ij}. She calls this measure "occupational distance", or D^{ij}, and defines it as follows:

$$\begin{aligned} D^{ij} &= \sum_{i=1}^{K} | P^{ik} - P^{jk} | \\ &= (P^{ii} + P^{jj}) - (P^{ij} + P^{ji}) + \sum_{i=1}^{K} | P^{ik} - P^{jk} | \end{aligned}$$

P^{ik} is the probability of moving from occupation *i* to occupation *k*, and, P^{jk}, P^{ij}, and P^{ji} are defined equivalently. *K* is the set of all occupations. P^{ii} and P^{jj} are the probability of staying within the same occupation *i* and *j*, respectively. This formula implies that the smaller the distance D^{ij}, the closer the two occupations or the greater the skills transferability. Hence, for occupations *i* and *j* to be close, or to have a high transferability of skills, they must have a close equality of movement between occupation *i* and *k*, and between occupation *j* and *k*. In other words, the main advantage of using the distance function rather than the probability of moving, P^{ij} is that it is not only a function of the probability of moving between occupation *i* and *j*, but also compares the probability of movement between occupation *i* and *j* and all other possible occupations as well. For example, in order for a technician and engineer to be similar, the probability of moving from a technician to any other occupations should be very similar to the probability of moving from an engineer to other occupations. Using D^{ij} thus adds a greater theoretical content to the measure of occupational skills transferability rather than the use of the probability of occupational switches, P^{ij} (Shaw, 1981).

As we can see, if occupation *i* and *j* are completely different (unrelated) in terms of skills transferability, then D^{ij} will be equal to 2 (i.e., all individuals stay in the same occupation such that $P^{ii} + P^{jj}$ is equal to 2, and the rest of the equation is equal to 0), and if they are exactly the same in terms of skills transferability, then D^{ij} will be equal to 0 (i.e., all individuals change their occupation such that all terms in the equation are equal to 0). Thus, we could scale the value of D^{ij} to be bounded between 0 and 1 as follows:

$$d^{ij} = 1 - (D^{ij} / 2)$$

Therefore, d^{ij} is proposed to be the measure of proportion of skills that are transferable across occupations ranging from 0 to 1.

d^{ij} is a symmetric matrix, $d^{ij} = d^{ji}$; the direction of the occupational movement does not matter. The skills transferability from occupation i to j is equal to that from occupation j to i, and d^{ij} measures the average transferability between these two directions of movement.

In this chapter, Shaw's occupational skills transferability is estimated at the 2-digit level of the 1980 occupational classification system.[1] To estimate it, I use the 1983, 1985, 1988, and1991 March CPS. This dataset provides the current and "one year ago" occupations of respondents, 18 years or older and not in school. The advantage of this dataset is that it is a very large dataset drawn on a random sample of over 60,000 households, which is weighted to be representative of the U.S. population. However, the short interval length of occupational switches could also produce the very high retention rates, and it provides only the change in the very short run (Shaw, 1984). Aggregating the 4 March CPS survey years, I have cross sectional data for 638,380 individuals. I delete individuals who do not have occupations both at the current year and one year ago. Thus, the final sample size is 303,022. Around 44.8 percent of the sample is female, and the average age is approximately 37 years old.

2.2 Ormiston's Skills Transferability Method

Ormiston (2006) develops an alternative method of estimating the occupational skills transferability that directly measures the skill content of jobs. In particular, he estimates the skills transferability based on the knowledge, skills, and abilities (KSAs) shared across occupations. The dataset that is used to estimate the skills transferability is the O*NET, the authoritative national database on vocational information coordinated by the United States Department of

[1] The more desirable category would be based on the 3-digit level. However, estimating the skills transferability based on Shaw's approach using the detailed 3-digit occupational categories is tedious. It results in almost 160,000 cell probability matrix with many cells with zero.

Labor.[2] O*NET data characterizes 900 distinct professions along 120 standardized knowledge, skill, and ability categories, as shown in Appendix Table A1.[3] The skills transferability measure is an estimated proportion of occupation-specific human capital that would be transferred from one's origin occupation to one's destination occupation, and it is derived by the computation of a ratio of shared KSAs between two occupations to the KSAs required within the origin occupation. Thus, two occupations, based on Ormiston's approach, are similar if they utilize or share all 120 dimensions of KSAs in the similar proportions.

The O*NET dataset scores the KSAs utilized in each profession along two separate indices: (1) the *level* of each KSA required of one to perform adequately, scored on a 1-7 scale, and (2) the *importance* of each KSA to the responsibilities of the occupation, scored on a 1-5 scale. This two-dimensional approach is imperative in capturing both the breadth and the depth of KSAs required in each profession (Ormiston, 2006). The product of the *importance* and *level* scores of 120 KSA dimensions within each occupation will generate a "point" within an occupation.

Using the KSAs for each occupation, I estimated the skills transferability by calculating the proportion of KSAs that would be transferred from one's origin occupation to one's destination occupation. I did so by computing the ratio of shared KSAs to total KSAs required within the origin occupation. Table 1 provides the knowledge score of an industrial engineer and human resource manager in "Administration and Management," "Engineering and Technology,"

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[2] O*NET dataset is available from http:// www.onetcenter.org/database.html#archive.

[3] Ormiston's occupational skills transferability is first based on the Standard Occupational Classification (SOC) and then is matched to the 2- and 3-digit occupational categories of the 1980 occupational classification system provided in the CPS. While there are some differences between these two systems, I carefully matched these categories with guidance from the CPS codebook supplement in order to prevent the recoding problems.

and “Sales and Marketing” categories. For example, an industrial engineer uses 16.01 points of the administration and management knowledge area, while the HR manager uses 19.68 points. Within this knowledge category, the two occupations share 16.01 points. While the industrial engineer can apply all 16.01 points of their “Administration and Management” knowledge in his/her role as an HR manager, the HR manager, on the other hand, can apply only a portion of his/her 19.68 points in a role as the industrial engineer, given the smaller requirement of “Administration and Management” knowledge in the engineering occupation. Using the transferability estimate outlined above, in this example, the transferability of the “Administration and Management” knowledge category from the industrial engineer position to the HR manager position is equal to 1 (16.01/16.01), while the transferability of the “Administration and Management” knowledge category from the HR manager position to the industrial engineer position is equal to 0.814 (16.01/19.68).

By summing this score within all 120 categories of KSAs for each pair of occupations, and then averaging the totals to provide equal weighting, I then can derive the 467 X 467 occupational skills transferability matrix based on the 3-digit U.S. census code as well as 45 X 45 matrix at the 2-digit level, representing the estimated proportion of occupational skills transferability.

3. Comparison of Shaw’s and Ormistion’s Estimates

Both Shaw’s and Ormiston’s skills transferability approaches have strengths and weaknesses. Shaw’s skills transferability is the market-based approach. It combines skill factors with demand factors as well as social factors. High demand for a given set of occupational skills will cause more movement into that occupation from individuals who are more distant because the demand curve and wages will be moving up. On the other hand, Ormiston's skills transferability is a technical-based approach, which is a pure measure of commonality of knowledge skills and abilities (KSAs) among occupations.

Compared with Ormiston's approach, the main pitfall of Shaw's estimation is it assumes skills transferability to be symmetric, in which the skills transferability from occupation *i* to *j* is equal to the skills transferability from occupation *j* to *i*. In other words, the direction of the skills transfer is irrelevant, and the d^{ij}, therefore, measures the average transferability values between these two directions of movement. This assumption might not be entirely reasonable, especially when moving from a more to less skilled occupation. It is less likely that the same proportions of skills are transferred as in the opposite direction (Shaw, 1984). For example, this approach implies skills transferability from nursing to being a doctor is the same as from being a doctor to a nurse. In reality, however, we would anticipate a doctor that later became a nurse could transfer more of the medical skill to a nurse but not vice versa. The same story holds for a university professor who later becomes a teacher as well. Also, a symmetric relation of the distance measure could obscure the fact that there are also non-negligible asymmetries in the skills transferability when comparing a move from occupation *i* to *j* to a move from *j* to *i*. Ormiston's skills transferability, on the other hand, is a non-symmetric method, in which the skills transferability from occupation *i* to *j* does not have to be equal to that from occupation *j* to *i*.

Another limitation of a market-based approach is that it must be driven by demand. If there is little demand for a given occupation, there will be little movement into it (i.e., low transferability), even from very similar occupations. As a consequence, it will mislead the estimates if we are interested in measuring the effect of the occupational switches on wages.

On the other hand, the main disadvantage of Ormiston's approach is that it is calculated purely based on the commonality of KSAs, and may not reflect actual labor market movement between occupations. In particular, this measure can yield a high value of skills transferability between two occupations although the movement between those two particular occupations rarely occurs in the market, such as the movement from a biologist to physicist, while Shaw's approach is based on the actual movement of individuals in the labor market reflecting both market and technical conditions. If the actual movement between two occupations is low, the skills transferability based on Shaw's method is more likely to approach zero. Another problem with Ormiston's measure could arise because the KSAs cannot possibly capture every single skill attribute of each occupation. Thus, there are other skill factors that are not captured in the KSAs that would explain the lower occupational mobility such as between a doctor and janitor. The subsequent section presents the estimation results of these two approaches.

4. Estimation Results

Table 2 presents the probability matrix of occupational movement (P^{ij}) for 10 selected occupations at the 2-digit level.[4] It suggests most of individuals stay in the same occupation between "one year ago" and current year. For example, 97 percent of individuals who work as engineers one year ago remain in the same occupation in the current year while only 0.02 percent becomes mechanics and repairers, and 0.1 percent becomes college teachers. The very high retention rate would result in the small value of skills transferability, d^{ij} (i.e., $P^{ii} + P^{jj}$ is very close to two). Table 3 demonstrates the estimated Shaw's skills transferability matrix for 10

[4] These 10 occupations are chosen from the different 1-digit occupational categories.

selected occupations. Not surprisingly, the estimated skills transferability across 2-digit occupations is relatively low and most of them are less than 10 percent. For example, the skills transferability from engineers to college teachers is approximately 0.027, suggesting that approximately 2.7 percent of occupational skills used by engineers could be able to transfer to the academics profession while around 2.3 percent would be able to transfer to mechanics and repairers. As mentioned above, the direction of the occupational movement is irrelevant for the skills transferability based on Shaw's method. Therefore, in this case the skills transferability from engineers to college teachers is equal to that from college teachers to engineers.

The average skills transferability estimate based on Shaw's approach in this sample is approximately 0.065 with a standard deviation of 0.148 (see Table 4). The highest occupational skills transferability is between "farm workers" and "freight, stock, and material handlers", which is around 0.567 while the lowest occupational skills transferability is between "lawyers and judges" and "health diagnosing occupations", which is 0.002.

Table 5 presents the Ormiston's skills transferability matrix for 10 selected occupations at the 2-digit level. For example, the skills transferability from engineers to college teachers is approximately 0.5, suggesting that 50.0 percent of KSAs used by engineers would transfer to the academic profession. On the other hand, only 21.7 percent of KSAs could be transferred from engineers to construction laborers. As opposed to Shaw's approach, the direction of occupational movement does matter for Ormiston's approach. While 71.9 percent of skills from executive managers could be transferred to engineers, 53.7 percent of skills from engineers could be transferred to executive managers.

The average skills transferability based on Ormiston's approach in this sample is approximately 0.564 with a standard deviation of 0.147 (see Table 4). The highest 2-digit occupational skills transferability is from “supervisors, proprietors, and sales” to “public administrators”, which is around 0.93 while the lowest occupational skills transferability is from “public administrators” to “construction laborers”, which is 0.186. The bottom of Table 4 also shows the summary of Ormiston’s skills transferability at the more detailed 3-digit level. The highest skills transferability is from “ushers” to “police and detectives”, which is around 0.998, and the lowest skills transferability is from “architects” to “garbage collectors”, which is around 0.051.

As we can see from Table 3 and Table 5, two approaches yield very different magnitudes of skills transferability. For example, Shaw’s estimate suggests that the skills transferability from engineers to college teachers is around 0.0271 while Ormiston’s estimate indicates the transferability is around 0.5. In spite of this difference, the estimated correlation between Shaw’s and Ormiston’s approach is approximately 0.45, indicating a positive and modestly strong correlation.

5. Conclusion

This chapter estimates the skills transferability applying Shaw’s and Ormiston’s approaches as well as discusses the strengths and weaknesses of each approach. These two approaches produce very different results of skills transferability although they have a fairly high correlation; therefore, the choice of measure could significantly impact the estimates of study.

On the one hand, since Ormiston’s skills transferability might not be able to capture all aspects of occupation skills, and there might be other skill factors that are not captured in the KSAs that would explain the lower movement between occupations, Shaw’s skills transferability might be preferred over Ormiston’s measure. On the other hand, if we believe that the lack of mobility is not due to skills transferability but rather to discrimination or other factors, then we want to use Ormiston's measure. For example, the reason workers do not change occupations such as from a janitor to doctor often has more to do with limited access to medical school or social class. In that case, it is factors other than skill that explain the lack of mobility, and we should prefer Ormiston's skills measure over Shaw's because Shaw's is contaminated with these social factors.

In the subsequent chapters, the estimates of these two approaches will be used to develop a new measure of occupational human capital based on Shaw’s (1984) model to examine the determinants of workers’ wages in Chapter 2 and used to determine the earnings losses following job displacement in Chapter 3.

Table 1. Score Categories Using to Calculate Occupational Skills Transferability.

	Score of 3 selected knowledge categories		
Occupation	Administration and Management	Engineering and Technology	Sales and Marketing
HR manager	19.68	1.03	5.99
Industrial engineer	16.01	23.50	9.76

Table 2. The Probability Transition Matrix (1983, 1985, 1989, and 1991 March CPS)

Initial Occupation (1980 code)	Destination Occupation (1980 code)									
	(2)	(4)	(9)	(11)	(17)	(22)	(25)	(34)	(41)	(44)
Executives, administrators (2)	0.941	0.001	0.001	0.000	0.003	0.000	0.000	0.003	0.000	0.000
Engineers (4)	0.006	0.970	0.001	0.000	0.001	0.000	0.000	0.000	0.000	0.000
Teachers, college and university (9)	0.007	0.001	0.916	0.001	0.001	0.001	0.000	0.001	0.000	0.001
Lawyers and judges (11)	0.004	0.001	0.001	0.983	0.001	0.000	0.000	0.000	0.000	0.000
Sales reps, finance, business (17)	0.012	0.000	0.000	0.001	0.924	0.000	0.001	0.002	0.000	0.000
Computer equipment operators (22)	0.003	0.000	0.001	0.000	0.002	0.916	0.002	0.001	0.002	0.001
Mail and message distributing (25)	0.003	0.000	0.001	0.000	0.002	0.000	0.925	0.002	0.002	0.001
Mechanics and repairers (34)	0.005	0.001	0.000	0.000	0.001	0.000	0.000	0.919	0.003	0.004
Construction laborers (41)	0.003	0.000	0.000	0.000	0.001	0.002	0.001	0.006	0.856	0.006
Farm workers (44)	0.004	0.000	0.000	0.000	0.002	0.000	0.001	0.014	0.008	0.829

Table 3. The Skills Transferability Matrix for 10 Selected Occupations (Shaw's Approach)

Initial Occupation (1980 code)	Destination Occupation (1980 code)									
	(2)	(4)	(9)	(11)	(17)	(22)	(25)	(34)	(41)	(44)
Other executives, administrators (2)	1.000	0.025	0.043	0.014	0.061	0.044	0.046	0.039	0.045	0.047
Engineers (4)	0.025	1.000	0.027	0.012	0.023	0.022	0.020	0.023	0.021	0.024
Teachers, college and university (9)	0.043	0.027	1.000	0.017	0.042	0.040	0.034	0.028	0.033	0.037
Lawyers and judges (11)	0.014	0.012	0.017	1.000	0.014	0.014	0.014	0.013	0.012	0.014
Sales reps, finance, business (17)	0.061	0.023	0.042	0.014	1.000	0.045	0.048	0.035	0.048	0.050
Computer equipment operators (22)	0.044	0.022	0.040	0.014	0.045	1.000	0.052	0.038	0.054	0.051
Mail and message distributing (25)	0.046	0.020	0.034	0.014	0.048	0.052	1.000	0.047	0.065	0.065
Mechanics and repairers (34)	0.039	0.023	0.028	0.013	0.035	0.038	0.047	1.000	0.076	0.092
Construction laborers (41)	0.045	0.021	0.033	0.012	0.048	0.054	0.065	0.076	1.000	0.558
Farm workers (44)	0.047	0.024	0.037	0.014	0.050	0.051	0.065	0.092	0.558	1.000

Table 4. Summary of Occupational Skills Transferability

Shaw's approach (2-digit)	From	To	Skills transferability
Mean			0.065
Standard Deviation			0.148
Most similar			
	Farm workers	Freight, stock, and material handlers	0.567
	Other handlers, equipment cleaners, and laborers	Construction laborers	0.558
	Forestry and fishing occupations	Freight, stock, and material handlers	0.548
Least similar			
	Lawyers and judges	Health diagnosing occupations	0.002
	Sales related occupations	Health diagnosing occupations	0.003
	Forestry and fishing occupations	Health diagnosing occupations	0.004
Ormiston's approach (2-digit)	**From**	**To**	**Skills transferability**
Mean			0.564
Standard Deviation			0.147
Most similar			
	Supervisors, proprietors, and sales	Public administrators	0.929
	Supervisors, proprietors, and sales	Supervisors-administrative support	0.884
	Sales representatives, finance and business	Public administrators	0.856
Least similar			
	Public administrators	Construction laborers	0.186
	Lawyers and judges	Construction laborers	0.188
	Lawyers and judges	Other transportation and material moving	0.193
Ormiston's approach (3-digit)	**From**	**To**	**Skills transferability**
Most similar			
	Ushers	Police and detectives	0.998
	Insulation workers	Electricians	0.996
	Shoe machine operators	Machinists	0.995
Least similar			
	Architects	Garbage collectors	0.051
	Chief executives and general administrators	Garbage collectors	0.082
	Psychologists	Garbage collectors	0.084

Table 5. The Skills Transferability Matrix for 10 Selected Occupations (Ormiston's Approach)

Initial Occupation (1980 code)	Destination Occupation (1980 code)									
	(2)	(4)	(9)	(11)	(17)	(22)	(25)	(34)	(41)	(44)
Other executives, managers (2)	1.000	0.719	0.650	0.626	0.570	0.538	0.352	0.298	0.210	0.442
Engineers (4)	0.537	1.000	0.500	0.469	0.413	0.464	0.285	0.313	0.217	0.378
Teachers, college and university (9)	0.684	0.704	1.000	0.678	0.560	0.557	0.339	0.289	0.199	0.433
Lawyers and judges (11)	0.692	0.695	0.707	1.000	0.563	0.536	0.336	0.265	0.188	0.409
Sales reps, finance, business (17)	0.795	0.776	0.745	0.717	1.000	0.659	0.456	0.364	0.258	0.507
Computer equipment operators (22)	0.667	0.767	0.662	0.599	0.576	1.000	0.454	0.410	0.304	0.522
Mail and message distributing (25)	0.754	0.806	0.707	0.664	0.697	0.795	1.000	0.573	0.485	0.669
Mechanics and repairers (34)	0.542	0.767	0.513	0.438	0.476	0.619	0.501	1.000	0.499	0.596
Construction laborers (41)	0.571	0.773	0.524	0.471	0.499	0.682	0.629	0.707	1.000	0.680
Farm workers (44)	0.651	0.760	0.621	0.550	0.537	0.646	0.496	0.513	0.416	1.000

Chapter 2

OCCUPATIONAL HUMAN CAPITAL AND WAGES: THE ROLE OF SKILLS TRANSFERABILITY ACROSS OCCUPATIONS

1. Introduction

The concept of occupational human capital has become particularly important in recent literature for understanding the wage growth over the lifecycle, wage inequality, and the distribution of earnings across the labor force (Sullivan, 2006; Zangelidis, 2007; Kambourov and Manovskii, 2009; etc.). For example, Kambourov and Manovskii (2009) find that five years of tenure in the current occupation on average increase wages by 12 to 20 percent. With few exceptions, the important contributions from most previous studies have focused on the role of occupation-specific skills (i.e., skills that would be lost or not be applicable whenever workers change occupations) and neglect the idea that skills could be transferred across occupations. Ignoring skills transferability might introduce a measurement error into the estimation and result in a misleading estimate of the effect of occupational human capital on wages. Therefore, in this chapter, I intend to examine the role of occupational human capital as well as skills transferability in the determination of workers' wages, applying Shaw's (1984) model. To my knowledge, this is the first study that applies Shaw's model to the study of wage determination.

I use data from 1979 through 2000 of the National Longitudinal Survey of Youth (NLSY) to estimate the share of wages that can be explained by variations in occupational human capital. This dataset provides detailed information about the employment of a nationally representative sample of young men and women (12,826 individuals) who were between the ages of 14 and 21 when first interviewed in 1979. In particular, the 2- and 3-digit occupation codes for each job in this dataset are used to create a series of occupation tenure variables for each person, and later to create a new measure of occupational human capital.

Building on Shaw's (1984) model, the first contribution of this chapter is to examine whether the workers' wages increased due to the skills transferred from the previous occupations. The findings show that controlling for the tenure at the current occupation, two additional years of skills accumulation transferred from the previous occupation on average increased wages by 1.2 to 2.6 percent. In addition, the new measure of occupational human capital incorporating skills transferability, or so-called *occupational investment*, is one of the important sources of wages, supporting Shaw's original work on wage determination. Specifically, the return to (3-digit) occupational investment relative to five years of occupational tenure could lead to a wage increase of 7 to 16 percent. This implies that the skills from the previous occupation are successfully transferred to the current occupational skills to increase wages. I also find that the general labor market experience accounts for a large share of workers' wages, which supports the importance of general skill accumulation. The second contribution is to analyze and compare the return to occupational human capital with other components of human capital. Overall, the results of this chapter demonstrate the positive and statistically significant effect of general, firm-, industry-, and occupation-specific human capital on wages. This chapter also presents the separate estimates for Shaw's and Ormiston's skills transferability at the 2-digit level. Overall, both approaches produce the fairly similar results. In particular, the return to 2-digit occupational investment relative to five years of occupational tenure based on Shaw's method increases wages by 6.2 to 13.3 percent, while the return to occupational investment relative to five years of occupational tenure based on Ormiston's method increases wages by 6.1 to 15.8 percent.

The analysis of this chapter serves as a next step toward understanding how occupations are related and how occupational human capital contributes to individuals' wages. In particular, the specification of this model allows us to quantify the importance of occupational skills from the previous occupations for wage determination, relative to other dimensions of human capital (e.g., general, firm-, and industry-specific human capital). In addition, it is particularly important for understanding wage growth over the lifecycle and the distribution of earnings across the labor force. For example, the wage-occupational specificity profile is a key source of the extent to which the wage power of individuals is tied to specific occupations, and it is important for assessment of the losses suffered by "displaced" workers (Kambourov and Manovskii, 2009). Little is still known about the losses experienced by workers who find re-employment in occupations that are not the same but are similar to their pre-displacement occupation, in which the occupational skills transferability is relatively high. Chapter 3 will explore this relationship.

This chapter is organized as follows. In Section 2, I summarize the literature on the return to several components of human capital, particularly occupational tenure. Section 3 describes the estimation of occupational human capital applying Shaw's (1984) model as well as the empirical methodology. Then, Section 4 discusses the data used in the main analysis. Section 5 presents the descriptive statistics and empirical results. Section 6 concludes and discusses some implications for future research.

2. Literature Review

The traditional human capital model (Becker, 1964; Mincer, 1974) decomposes skills into two components. The first component is "general skills," defined as skills that are productive and transferable across different firms and usually measured as years of labor market experience. The second component is “firm specific skills,” which are defined as skills that are productive at only one firm, generally measured as years of work in the current firm, and nontransferable across firms. Typically, workers acquire these specific skills through both formal and informal (specific) on-the-job training, familiarity with employers’ processes, production lines, or business culture, and as the amount of these skills increases with tenure at the firm, the wages also rise.

Empirical studies generally find a positive relationship between years of labor market experience and wages. This positive relationship is due at least in part to the significant amount of (general) on-the-job training that occurs both formally and informally on the job (Becker, 1964). However, the Current Population Survey (CPS) and other cross-sectional datasets used in past studies lack the information on actual work histories needed to precisely measure the market experience. Instead, researchers use a proxy measure called “potential experience,” which is calculated as an individual’s age minus years of education minus six.[5] Although this measure is commonly used in the previous literature, it is a poor proxy for market experience for at least two reasons. First, it assumes that individuals immediately enter the labor market after they leave school (Altonji and Blank, 1999). However, in reality, many individuals, particularly women, postpone entering the labor market by one or more years. Second, potential experience assumes continuous work histories. This assumption is also implausible in reality, especially for women because many of them experience interruptions throughout their careers, such as leaving the labor market during their child-bearing period (Regan and Oaxaca, 2009). Ignoring these interruptions could introduce measurement error and thus bias estimation results. Longitudinal datasets such as the Panel Study of Income Dynamics (PSID) and National Longitudinal Survey

[5] I use six because, in general, people do not start school until age of six years old.

of Youth (NLSY), on the other hand, allow researchers to construct a more precise "actual experience" measure of general human capital. Regan and Oaxaca (2009) compare both measures to examine the gender wage gap. They show that the measure of market experience used is important. In particular, when a potential experience variable is used, almost all of the gender wage gap is unexplained. However, when an actual work experience measure is used, around 30 percent of the gender wage gap is attributable to differences in the mean values of the regressors for males and females. As a result, in this analysis, I will apply the precise "actual experience" available from the NLSY to the estimation of workers' wages.

There are also other studies that emphasize the impact of firm-specific human capital, which is generally measured by employment duration with a current firm, on workers' wages. They have found a large and positive effect of job seniority (firm tenure) on wages; i.e., the increase in wages with tenure, holding general experience constant, is attributed to the workers' investments in firm-specific skills (for example, Bartel and Borjas, 1981; Borjas, 1981; Willis, 1986; Topel, 1991). Topel (1991) finds that, on average, ten years of job tenure with one's current employer increases one's wages by over 25 percent. Willis (1986) finds that one additional year of job tenure is correlated with a 2 to 3 percent increase in wages. This finding, therefore, provides the evidence that human capital is highly firm specific, which implies that the transferability of human capital is very limited.

However, the idea that workers' wages rise as their employment duration with the same employer increases has been controversial. Much of the debate has focused on the potential endogeneity of the tenure variable (for example, Altonji and Shakotko, 1987; Abraham and Farber, 1987; Topel, 1991; Altonji and Williams, 1997). The tenure variable will be endogenous if it is correlated with unobserved individual and job characteristics that affect wages. For example, if workers who have higher (unobserved) ability tend to stay in the firm longer to accumulate more specialized skills and receive higher wage returns than less able counterparts, then the estimate of firm tenure would be positively biased (Neal 1998). To address this endogeneity problem, Altonji and Shakotko (1987) use the PSID dataset and apply an instrumental variable (IV) method. Their IV is constructed as the deviation of the tenure measure from its mean within a worker firm match.[6] Their OLS estimates are slightly lower than Topel's (1995) study, in which ten years of firm tenure increases wages by 18 percent. However, when applying the IV method, they find the partial effect of firm tenure on wages is small and statistically insignificant. Specifically, on average, ten additional years of firm tenure will increase wages by only 6.6 percent, with much of the increase occurring in the first year on the job.

In addition to the endogeneity problem associated with the firm tenure measures, other more recent studies have critiqued the appropriateness of decomposing a worker's total labor market experience into only two components: firm-specific and general experience, as in traditional human capital theory. Instead, these studies posit skills and experience obtained may also be specific to certain industries or occupations, and they are more likely to contribute to the workers' wages, rather than general or firm-specific skills. Neal (1994) and Parent (2000) provide evidence to suggest that industry-specific human capital is much more important than firm-specific human capital, and the correlation between the workers' wages and firm tenure might also be explained to some extent by the omitted years in the industry. Using the NLSY and PSID, Parent (2000) finds a very strong effect of industry-specific human capital, measured by

[6] For example, the instrumental variable for employer tenure $Tenure_{ijt}$ is $Tenure_{ijt} - \bar{T}enure_{ij}$, where $\bar{T}enure_{ij}$ is an average tenure within individual *i* working for employer *j* across time period *t*. By construction, the instruments are orthogonal to the unobserved worker ability and job match.

industry tenure, on wages. In particular, he finds that ten years in an industry increases wages over 20 percent. Looking at industry-specific human capital and job displacement, Neal (1994) finds that displaced workers who switch 1-digit industry following displacement, on average, suffer greater wage losses than those who find new jobs in their pre-displacement industry. In addition, the post-displacement wages among displaced workers who stay in their old industry increase more sharply with the pre-displacement tenure and years of labor market experience than among those who switch industries. However, in the concluding section of his paper, he raises the possibility that his results may reflect the importance of skills that are not truly specific to given industries, but rather specific to a set of skills associated with occupations (Neal, 1995).

Thus, aside from the role of industry in explaining the wage determination, many studies have examined the effect of occupational skills, generally measured by tenure at the current occupation, on wages. The common conclusion across studies using different datasets is that skills specific to occupation are likely to be an important source of wage determination. The magnitude of these estimates, however, varies by data and empirical specifications. Using data from the PSID Retrospective Occupation-Industry Supplemental Data Files (Retrospective files) from 1968–1993, Kambourov and Manovskii (2009) find that five additional years of occupational tenure increases wages by 12 to 20 percent, all else being equal. In addition, they also find that when an individual's occupational tenure is included in the wage equation, firm and industry tenures explain little of the variation in wages, implying that some portions of both firm- and industry-specific human capital have been captured by the occupational dimension of human capital. Zangelidis (2007) extends Kambourov and Manovskii's (2009) study using the British Household Panel Survey (BHPS) from 1991–2001. Although he finds a much smaller estimated effect of occupational tenure than Kambourov and Manovskii's (2009) study, the occupational tenure effect is still statistically significant and larger than the estimated effect of firm tenure. Specifically, five years of occupational tenure leads to an estimated increase in wages of around 2.5 percent, all else equal, while five years of firm tenure increases wages by 1.8 percent. In addition, he also finds little support for the role of industry tenure in wage determination. Schmieder (2007) uses a German administrative dataset, the IAB Employment Sample IAS (Regional File) from 1975–2001, and finds that the return on five years of occupational tenure is around 2 to 9 percent. While the return to firm tenure is very sensitive to the inclusion of occupational and industry tenure variable, the result still shows the significant effect of return to firm tenure, which is around 3 percent, all else equal. He explains that the reason that the return to occupational tenure is less in U.S. datasets (e.g., PSID, NLSY) is because there are large institutional differences between the German and the U.S. labor markets (e.g., the importance of unions, the German apprenticeship system, etc.) that make it possible for wage growth over the career of a worker to be significantly different. For example, in the German labor market, workers have already acquired most occupational skills during the apprenticeship period before they actually enter the full-time labor market (Schmieder, 2007). In contrast to Kambourov and Manovskii's (2009) and Zangelidis's (2007) results, Sullivan (2006) uses data from the NLSY and estimates that both occupation and industry specific human capital are key determinants of wages. Specifically, five years of occupational tenure, on average, increases wages by 6 to 13 percent, all else equal, and five years of industry tenure increases wage by 4 to 6 percent, all else equal, while the estimated effect of firm tenure is very small and statistically insignificant. Goldsmith and Veum (2002), on the other hand, use the NLSY and find that all components of human capital, including firm, industry, and occupational tenures, are estimated to have a positive and significant effect on individuals' wages. For example, they find that the workers' wages rise by 2.6 to 2.8 percent if they stay at their current firm for an additional year while an additional year of experience in the same occupation increases wages by 2.5 percent, and an additional year of experience in the same industry raises wages by 2 percent.

In summary, these studies of occupational tenure on wage determination find that including occupation tenure has large effects on the estimated return for firm tenure in wage regression. In particular, with few exceptions, they show that when the occupational tenure is included in the wage equation, firm tenure has little impact on explaining the variation in wages. However, the magnitude of return to occupational tenure varies considerably across studies depending on the datasets used. Taken together, the above studies indicate that the traditional view of human capital, where skills are either firm specific or general, might not be appropriate. Instead, it is likely that a significant component of worker skills is specific to either industry or occupation, and these industry- or occupation-specific skills are an important determinant of workers' wages. This finding has important labor market implications. For example, it suggests that wage losses associated with losing a job with a particular firm might be lower if a worker is able to stay in the same occupation (industry) to preserve and continue accumulating occupational (industry) specific skills.

All of the above studies, however, use occupational tenure as a proxy for occupational human capital in wage determination analysis. Using occupational tenure does not account for differences in the skills transferability across occupations. In other words, the occupational tenure variable will be endogenous if it is correlated with the omitted occupational skills transferability from the previous job that also affects wages. Therefore, the use of occupational tenure in lieu of more precise measures of occupational human capital may introduce a measurement error into the estimation and thus bias the results.

Shaw (1984) is the first one who recognized the importance of transferability of occupational human capital in establishing particular labor market outcomes. More specifically, Shaw notes that the return to the stock of human capital from the former occupation is not completely foregone in the midst of an occupational switch. Instead, the return to one's human capital stock depends on the degree of transferability of skills from one occupation to the next. She hypothesizes that skills acquired in a particular occupation are portable across firms, making them "occupation specific" rather than "firm specific." Unlike the case of general human capital, individuals would be able to transfer only a certain amount of their occupation-specific human capital stock in the event of an occupational change, and that amount inherently depends on the degree of "transferability" between the two occupations (Shaw, 1984). For example, most of the skills acquired as an engineer may not be transferable to a career as a doctor, while the skills acquired as an accountant may have a high degree of transferability to a job as an actuary. Thus, occupational human capital, based on Shaw's definition, is neither completely general nor purely specific, but partially transferable across occupations.

In spite of Shaw's findings and contributions, only a few recent studies have started to focus on the importance of skills transferability. For instance, Lazear (2009) introduces a novel theoretical model called the "skill-weight" approach, suggesting that all skills are general across firms, but each firm might require a different combination of skills. Thus, the amount of human capital transferability across firms depends on the difference in skill requirements between the old job and the new job. Gathmann and Schönberg (2010) use the repeated cross-section *German Qualification and Career Survey* to estimate the transferability of three aggregate groups of skills (analytical, manual, and interactive) across 64 occupations. Their results show that individuals are more likely to move to the occupations with similar skill requirements, and more than 40 percent of their wage growth can be attributed to the proportion of these portable skills. Building on Shaw's (1984) idea, Ormiston (2006), uses the O*NET dataset to develop a transferability matrix of knowledge, skills, and abilities (KSAs) across occupations, and then he applies this transferability matrix to examine occupational movement associated with displacement in the manufacturing sector. With the role and application of skills transferability, there have been only few studies that incorporate the idea of skills transferability across occupations into the framework of wage determination process. Thus, in this chapter, I intend to develop a new measure of occupational human capital that directly attaches the value of occupational skills transferability, estimated in Chapter 1, to the occupational tenure to examine wage equation.

Given the growing acceptance of occupational human capital role but the remaining inadequacy of the occupational human capital measure commonly used (i.e., occupational tenure), it is necessary to revisit this topic. In this chapter, I will add to the findings in the previous literature by developing a conceptually better proxy for occupational specific human capital, based on Shaw's model, that incorporates skills transferability rather than occupational tenure and applies it in wage determination. My proposed analysis will also use a rich sample of individuals, the NLSY, which helps to more precisely estimate the impact of occupational human capital on the workers' wages as mentioned above. The following section describes the estimation of proposed occupational human capital measure as well as the methodology used in this analysis.

3. Empirical Methodology

3.1 The Estimation of Occupational Human Capital Measure (Occupational Investment)

This section describes the estimation of a new occupational human capital measure—*occupational investment*, based on Shaw's (1984) model. Consider an individual changes occupations from occupation *i* to occupation *j*, and γ^{ij} percent of his or her skills in occupation *i* are transferred to occupation *j*. During work in occupation *i*, the individual accumulates occupational specific investment that equals $\tilde{K}^{i}$. Therefore, combining the definitions of skills transferability and occupational specific investment, the individual's accumulated quantity of "occupational investment," which is the accumulation of skills an individual acquires to perform work within an "occupation" at time *t* is defined as:

$$K_t^j \equiv \tilde{K}_t^j + \gamma^{ij}\tilde{K}_{t_{j-1}}^i + \ldots + \gamma^{gj}\tilde{K}_{t_{g-1}}^g \qquad (2.1)$$

where $\tilde{K}^{j}$, $\tilde{K}^{i}$,…, $\tilde{K}^{g}$ represent stocks of occupational specific investment for the current occupation *j*, *i*,…,*g*, respectively. Define $\tilde{K}_t^j \equiv \sum_{h=t_j}^{t} k_h^j$ for k_t^j = the percent of full income invested in occupation *j* in year *t*, or the intensity of investment.[7] The skills transferability, γ^{ij} and γ^{gj}, are the percent of skills transferred from occupation *i* to *j* and *g* to *j*, respectively. t_j and t_g are the years of entry into occupations *j* and *g*. In other words, the occupational investment in occupation *j* is a weighted sum of the individual's accumulated quantities of occupation-specific

[7] In this Chapter, I use a slightly simplified version of Shaw's (1984) model to capture the skills transferability only from the most previous occupation. The original Shaw's model captures the skills transferability from all previous occupations.

investment in the current and previous occupations, where the weight is the transferability parameter ($\gamma^{ij}, \ldots, \gamma^{gj}$).

For simplicity, the complete individual's occupational history, $K_t^{\,j}$, can be estimated in the reduced form for each individual in the following way:

$$Occt_t^{\,j} = (occ\_tenure_{t(j)}^{\;\;j}) + \hat{\gamma}^{ij}\,(occ\_tenure_{t(i)}^{\;\;i}) \qquad (2.2)$$

γ^{ij} is a proxy for the "skills transferability" from occupation *i* to *j* (either by Shaw's or Ormiston's approach, developed in Chapter 1). $occ\_tenure_{t(j)}^{\;\;j}$ and $occ\_tenure_{t(i)}^{\;\;i}$ are the years of tenure in the current occupation *j* and the first previous occupation *i*, respectively. Thus, $Occt_t^{\,j}$ represents an occupational investment that includes skills from the current occupation *j* and some proportion of skills from the first previous occupation *i*. In addition, $Occt_{t+1}^{\;\;j}$ = 1+ $Occt_t^{\,j}$ for individuals who do not change occupation (occupational stayers) and $Occt_{t+1}^{\;\;j}$ =1+ $\hat{\gamma}^{ij} * Occt_t^{\,j}$ for individuals who change occupation (occupational switchers).

Parent (2000) constructs two types of (industry) tenures, including *continuous* and *non-continuous* spells. The continuous spell is measured by the consecutive number of years an individual has been in the same industry, including tenure with the current firm. If an individual changes firms to take another job in the same industry, he/she still adds one more year in that industry, whereas if he/she gets another job in a different industry, his/her tenure in that industry will reset to zero. On the other hand, for the non-continuous spells, if an individual changes to a new job that is not in the same industry as the job he/she just left but is in the same industry as some other previous job, then the industry tenure is not reset to zero. Instead, it is reset to the level of industry tenure of that prior job. The main difference between these two types can be considered as reflecting different depreciation rates of (industry) human capital, in which the continuous spells correspond to the case that the (industry) specific human capital depreciates rapidly after leaving an industry. On the other hand, the non-continuous spells can help increase the variance in the tenure that is required to identify the tenure coefficient (Parent, 2000). In line with the ideas of skills transferability that assumes less skills depreciation, in the estimation of my proposed occupational human capital measure, I focus only on the non-continuous spells. Further details on the construction of tenure measures and other variables can be found in Appendix B.

To illustrate, consider a worker with ten years of market experience. This worker had worked at occupation A for six years before entering his current occupation (occupation B). Assume that the skills transferability parameter from occupation A to B is 0.3. Thus, his current occupational investment in occupation B is 5.8 [4.0 + (0.3)*(6.0)].

To summarize, this measure of the occupational investment variable is a function of the number of years in each occupation (occupational tenure), and the transferability of skills among occupations. Note that if instead we assume the skills transferability is zero (i.e., occupational skills are depreciated completely during the occupational switches), then the occupational investment ($Occt_t^{\,j}$) will be equal to the years of experience in the current occupation, which is just the occupational tenure that has been applied in the prior studies (for example, Sullivan, 2006; Zangelidis, 2007; Kambourov and Manovskii, 2009). The subsequent section describes the empirical framework used in this analysis to examine the workers' wages process.

3.2 Wage Determination

First, I estimate a wage equation that considers the effects of general, firm-, and industry-specific human capital using the OLS method as follows.

$$\ln W_{ijdt} = \beta_1 firm\_tenure_{ijt} + \beta_2 exper_{it} + \beta_3 ind\_tenure_{idt} + \gamma' X_{ijdt} + \upsilon_{ijdt} \qquad (2.3)$$

where $\ln W_{ijdt}$ is the natural logarithm of real hourly wage ($1979) of worker *i*, working at firm *j*, industry *d*, and in time period *t*. $firm\_tenure_{ijt}$ denotes the current firm tenure (in level and squared terms), $exper_{it}$ is the "actual" labor market experience (in level and squared terms). ind_tenure_{idt} denotes the 2- or 3-digit industry tenure at industry *d* (in level and squared terms), and X_{ijdt} is a vector of control variables containing worker and job characteristics including years of education, age, marital status, major occupation and industry dummies, SMSA, year dummies, region, a dummy variable indicating whether an individual works at a current firm more than one year,[8] and the skills intensity at the current occupation including *SVP*, *TQ*, or *JobZone*, (see Appendix C for the discussion and estimation of these skills intensity measures). For a complete definition and construction of control variables, see Appendix B. υ_{ijdt} is a standard *iid* error term capturing unobserved individual characteristics, such as innate ability or motivation, and it is assumed to be uncorrelated with all the regressors. If the general, firm-, and industry-specific skills positively contribute to the wage determination, then β_1, β_2, and β_3 are expected to be positive.

[8] The reason for including this variable is that the first year of work with an employer typically requires more investment in job-related skills (Parent, 2000). In particular, this variable would be expected to be positive if investment in firm-specific skills rapidly increases at the beginning of a job.

Next, in order to examine the role of occupation-specific skills in the accumulated work experience, consider the following wage equation.

$$\ln W_{ijdqt} = \beta_1 firm\_tenure_{ijt} + \beta_2 exper_{it} + \beta_3 ind\_tenure_{idt} + \beta_4 occ\_tenure_{iqt} + \gamma' X_{ijdqt} + \upsilon_{ijdqt} \quad (2.4)$$

where occ_tenure_{iqt} represents the 2- or 3-digit occupational tenure of individual i at current occupation q as of time t (in level and squared terms). Hence, β_4 represents the effect of occupational tenure on the average of workers' wages. If longer occupational tenure increases workers' wages, then β_4 will be positive as well as the coefficients of other variables representing workers' stock of human capital. If labor market experience is completely general, then a change in occupations or industries should not matter (i.e., the magnitude of coefficient of experience should be slightly affected). In contrast, if a portion of the experience effect reflects occupational or industry specific skills, then adding a control for occupational (industry) tenure should reduce the magnitude of experience. In addition, if the occupational (industry) tenure plays a significant role in wage determination, then we would expect that including occupation (industry) tenure into the wage equation would also decrease the magnitude of the firm tenure's effect on wages, since some proportion of the estimated firm tenure effect would be attributed to both industry and/or occupation tenures that workers have accumulated in work, not only firm-specific skills. In other words, we would expect the magnitude of β_1 and β_2 in Equation 2.4 to be smaller than that of β_1 and β_2 in Equation 2.3.

To address the issue of different degrees of skills transferability across occupations, Equation 2.4 replaces the occupational tenure measure with the measure of occupational investment as follows.

$$\ln W_{ijdqt} = \beta_1 firm\_tenure_{ijt} + \beta_2 exper_{it} + \beta_3 ind\_tenure_{idt} + \beta_4 Occt_{iqt+} \gamma' X_{ijdqt} + \upsilon_{ijdqt} \quad (2.5)$$

where $Occt_{iqt}$ is the proposed measure of occupational investment (both in level and squared terms). In other words, β_4 is the estimated rate of return to one year of occupational investment relative to occupational tenure. Thus, if this new measure of occupational human capital contributes to the wage determination, then we would also expect β_4 to be positive.

However, the return to all of the tenure measures as well as occupational investment may be affected by the presence of various forms of unobserved heterogeneity across individuals and across job matches. These unobserved differences across individuals such as innate ability, motivation, as well as quality matches of the job, may bias the estimated return to human capital measures. For example, if individuals with high unobserved ability who earn a high wage are more likely to stay in the same occupation to obtain occupational skills, then the estimated return to occupational tenure or occupational investment based on a simple OLS regression will be biased up. Unfortunately, it is very difficult to eliminate all sources of potential biases introduced by these unobserved heterogeneity. To my best knowledge, there is no "best" way to eliminate all of the potential biases. In this chapter, I apply the fixed effect estimation (FE) to eliminate some sources of unobserved heterogeneity. The major advantage of FE method is on the ability to control for all characteristics of individuals in the model that is constant over time even without measuring them. FE method eliminates potentially large sources of bias and instead makes comparisons within individuals (Allison, 2005)

In summary, the analysis of occupational investment's effect on the workers' wages relies on the careful measurement of occupational investment, including skills transferability, and I propose that moving from the occupational tenure measure to my proposed measure of occupational investment incorporating skills transferability across occupations will correct for the measurement error and unbiasedness as well as provide more precise estimates of the contribution to wages. The next section explains the main dataset used in this analysis.

4. Data

The main dataset in this chapter is the National Longitudinal Survey of Youth (NLSY). It is a longitudinal dataset (1979–2008) that contains detailed information about the employment and education experiences of a nationally representative sample of young men and women (12,826 individuals) who were born between 1957 and 1964. The participants were between the ages of 14 and 21 when first interviewed in 1979 (and thus were 35–42 years old in 2000). The participants were interviewed, typically in their homes, annually through 1994 and are currently interviewed on a biennial basis. In this analysis, I use the data from 19 survey years, 1979–2000. The primary feature of this dataset is that it provides a weekly employment record that contains information about the durations of employment spells, including the starting and ending dates for all jobs, along with the wages, hours of work, and 3- and 2-digit U.S. Census occupation and industry codes for each job. These occupation and industry codes for each job are used to create a series of occupation and industry tenure variables for each individual in the sample. The main advantage of this dataset is that it covers the early labor market experience when most change occurs and when career decisions are likely to be most important.

This chapter uses the NLSY data ranging from 1979 to 2000 and focuses on white males who are above 18 years old.[9] These sample restrictions closely follow those imposed in Parent's

[9] This study uses only the data through 2000 to reduce the inconsistency of the coding format. Since 2000, both occupation and industry codes have been changed from the 1980 Census code to the 2000 census code.

(2000) study, except that the occupation and industry switches within a particular firm are also considered the genuine mobility.[10] Individuals who are self-employed, serving in the military at any time, or employed in the agricultural sector or public sector are all excluded from the sample in that particular year. Further, individuals who leave the survey forever after the first interview in 1979 such that there has been no information of their work histories are excluded from the sample. I also delete individuals who return to school on a full-time basis within six years. Details on sample restriction are provided in Appendix Table B1.

Based on the complete labor market history of the individuals since the first time they entered the labor market, I was able to construct all human capital measures, including actual labor market experience, firm tenure, industry tenure, occupational tenure, and occupational investment. In particular, the firm tenure variable measures the length of time a worker has worked with his/her current or most recent employer until the date of interview. This study also uses an actual experience variable as opposed to the potential experience variable used in many prior studies, and it measures the total work experience an individual has accumulated in the labor market up to the date of interview. Both occupational and industry tenures (at the 2- and 3-digit levels) measure the years an individual has been working in a particular occupation or industry.

Since the measure of occupational (industry) tenure is one of the key variables in this analysis, it is important to realize that there are problems of measurement error inherent in identifying "true" occupational switches. The occupational coding procedure in the NLSY (and

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[10] Some individuals report changes in industry and/or occupation without changing jobs (firm). While these changes are more likely to happen for occupation changes within firms, it is almost impossible to change industries within a firm (Parent, 2000). Also, there is no way to differentiate between real occupation or industry changes and coding errors in the data. Parent (2000) solves this problem by restricting the industry code to be the same within a firm.

also in other datasets such as the CPS) uses coders to assign particular occupation codes from the information given by survey participants. The information usually includes a brief description of the job. There is evidence of substantial measurement error in assigning these codes, especially at the more detailed 3-digit level (Kambourov and Manovskii, 2009). The errors in the NLSY occupation and industry codes may contaminate the analysis and lead to a false interpretation of occupational (industry) human capital effect on wages. Going from the 3- to 2- digit code might help reduce to some extent the measurement error. Thus, in this analysis, I construct occupation (industry) tenure at both 3- and 2- digit levels.

Observations with missing data on the variables used in the wage equation are excluded for the particular sample year. In some cases, the occupation and industry codes are missing because individuals refused to answer the question about the type of work they have performed. Also, they could be missing because errors were made in processing the descriptions of individuals' jobs (Neal, 1999). After deleting all missing information on the main variables used in the analysis, the sample is an unbalanced panel containing a total of 26,818 observations on 2,309 individuals.

5. Empirical Results

5.1 Descriptive Statistics

In this section, I first describe occupational mobility among employed workers from 1979 to 2000. In this case, I define occupational mobility as a fraction of employed workers who report a current occupation differently from their most recent job in the previous year. Figure 1 shows that, on average, the percentages of employed workers who in any two consecutive years change the 3-, 2- and 1-digit occupations are approximately 62.5, 51.4, and 41.8 percent, respectively and are generally falling over time as the cohort ages. Note that the discrete drop in mobility around 1992–1993 is likely a data artifact associated with a change from paper- to computer-based survey administration. [11] The information in Figure 1 has two important implications. First, it illustrates that we do observe that people change more often within 1-digit occupations, and most often at the 3-digit level. Second, it suggests that changes in occupation are very common and tend to occur early in a worker's career, especially for young workers (i.e., they are not only 'job shopping', but also 'occupation shopping'). Less occupational mobility over time might be because the accumulation of occupational skills makes occupational switches increasingly costly. Also, workers might be able to gradually locate better and better occupational matches as time spent in the labor market increases (Gathmann and Schönberg, 2010).

Table 6 presents the descriptive statistics of the key variables of this study. It indicates that the sample of white males earns an average of 5.7 per hour in 1979 dollars. In this sample, workers stay at the same 3-digit level occupation for an average of 2.45 years, which is lower than the corresponding industry tenure. The fact that occupational tenure is lower than industry tenure at both 3- and 2- digit levels suggests that workers are more likely to move across occupations than industries. Regarding general and firm-specific human capital, the average firm tenure is around 3.41 years, and workers have spent, on average, 8 years in the labor market. Note that the firm tenure is slightly higher than both occupational and industry tenure. This interesting finding would be missed if I did not allow for occupational and industry movement within firms. An average 3-digit occupational investment is higher than the occupational tenure by about one year. This emanates from an additional value of skills transferability from the

[11] Industry mobility patterns are quite similar to Figure 1 even though a higher percentage of workers tend to stay in the same industry.

previous occupation. On average, the individual in this sample changes firms about four times between these periods. The average number of years of education in this sample is low, around 13 years, because the analysis focuses on individuals who started their careers early in the labor market. (See Appendix Table B2 for the complete descriptive statistics of variables used in this analysis.)

Table 7 presents the correlation among the key human capital variables. In general, it indicates that the human capital measures are positively correlated. For example, the correlation between firm tenure and labor market experience is around 0.54, while the correlation between firm tenure and occupational tenure is somewhat lower, around 0.37. Again, this discrepancy appears because I allow occupational movement within firms to occur in the data. From an econometric standpoint, since these human capital measures are highly correlated with one another, the upward bias in one variable is likely to induce a downward bias in the other estimates of the tenure slope as well (Altonji and Shakotko, 1987). Therefore, it requires some careful interpretation of these measures. The following section presents empirical results examining the role of occupational human capital on wage determination.

5.2 OLS Regression Results of the Wage Equation

The empirical results from the basic OLS regression are reported in Table 8. Column (1) presents the standard wage equation with wages as a function of human capital and includes the actual labor market experience (general human capital), firm tenure (firm-specific human capital), and industry tenure (industry-specific human capital). The OLS coefficient estimates for experience and experience^2, firm tenure and firm tenure^2, and industry tenure and industry tenure^2 are 0.0567 and -0.0008, 0.0207 and -0.0008, and 0.0244 and -0.0009, respectively. As we can see, the coefficients of these three components of human capital are all statistically significant at the 1-percent level. This suggests that wages increase with labor market experience, firm tenure, and industry tenure though at a decreasing rate across workers, and that the workers' investment in the general, firm-, and industry-specific human capital each make distinct contributions to the workers' wages.

Column (2) adds the occupational tenure into the wage equation. The OLS coefficient estimates for occupational tenure and occupational tenure^2 are 0.0299 and -0.0009. In this specification, the occupational tenure has a fairly strong and positive effect on workers' wages. Also, the quadratic term of occupational tenure is negative and statistically significant at the 5-percent level, indicating evidence of a diminishing effect of occupational tenure on wages. In addition, the effect of occupational tenure on wages is larger than that of industry and firm tenures. Compared to Column (1), including occupational tenure measures into the wage equation also lowers the coefficient estimates of experience, firm tenure, and industry tenure as well (i.e., the coefficient estimates for experience and experience^2 firm tenure and firm tenure^2 and industry tenure and industry tenure^2 are reduced from 0.0567 and -0.0008 to 0.0528 and -0.0007, from 0.0207 and -0.0008 to 0.0183 and -0.0007, and from 0.0244 and -0.0009 to 0.0170 and -0.0007, respectively). Following Altonji and Shakotko (1987), the relationship between tenures and wages is summarized by calculating the effect of the first two and five years of tenures on the wages. This is reported in Table 9. For example, the first five years of occupational tenure based on OLS increase wages by 12.6 percent; the first five years of industry tenure increase wages by 6.9 percent; the first five years of firm tenure increase wages by 7.3 percent, and the first five years of labor market experience increase wages by 24.6 percent.

Column (3) of Table 8 includes the occupational skills transferability measure into the wage equation. The coefficient of skills transferability is 0.0127 and statistically significant at the 1-percent level. This indicates the important effect of previous occupational skills on wages across workers. In particular, two additional years of occupational skills from the previous occupation, on average, increase the current wages by 2.6 percent, controlling for the current occupational tenure. Note that including occupational skills transferability only slightly lowers the coefficient estimates of occupational tenure.

Column (4) to (6) independently includes the measure of skills intensity in the current occupation, either *SVP*, *TQ*, or *JobZone*, into the wage equation. As we can see, each of these three skills intensity measures produces a fairly similar effect on wages, and it is statistically significant at the 1-percent level. For example, the *SVP* coefficient translating into the elasticity at the mean equals 0.09[0.0177*5.13]. In other words, a 10-percent increase in the *SVP* at the mean increases wages by about 9 percent. This indicates the important effect of the occupational skills acquisition on determining wages across workers. Note that there is similar change in other coefficient estimates when adding each of these three skills intensity measures. Therefore, for ease of presentation, I will present the results hereafter using only the *SVP* measure.

Column (7) replaces the occupational tenure measure with the occupational investment measure. The coefficient estimates of occupational investment and occupational investment^2 are 0.0291 and -0.0007. As we can see, the linear term of occupational investment is positive and statistically significant at the 1-percent level while the squared term is negative and statistically significant at the 10-percent level. This indicates that the occupational skills from the previous occupation are successfully transferred to the current occupational skills so that the investment in both current and previous occupational skills increases the workers' wages, though at a decreasing rate. The more total experience the worker has in the occupation profile, the higher his/her wages will be. Column (8) includes the *SVP* measure into the wage equation. As we can see, the coefficient of *SVP* is still positive and statistically significant at the 5-percent level, and there is little change to other coefficient estimates, which means that the skills intensity is independently important for wage determination after controlling for other human capital measures.

5.3 FE Regression Results of the Wage Equation

As mentioned earlier, there is the possibility of unobserved heterogeneity bias across individuals and jobs that occurs when (pooled) cross-sectional results are interpreted as a true estimate for the average individual over time. Table 10, therefore, presents the FE results. As we can see, except for labor market experience, other FE coefficient estimates of human capital measures are smaller than those of OLS. This upward bias of OLS coefficient estimates is probably from the positive correlation between the unobserved worker and job characteristics and tenure measures that also affect wages. In particular, compared to Column (3) of Table 8, Column (3) of Table 10 shows that the FE coefficient estimates for occupational tenure and occupational tenure^2 are reduced from 0.0311and -0.0009 to 0.0160 and -0.0006, and the coefficient estimates for occupational skills transferability is reduced from 0.0127 to 0.0059, with a smaller t-statistic but still statistically significant at the 10-percent level. In particular, two years of skills accumulation from the previous occupation, on average, increase the workers' wages by about 1.2 percent, all else equal. Despite about a 50 percent reduction in the coefficient estimate, the skills transferability from the previous occupation is still an important source of workers' own wages over time.

Column (4) presents that the FE coefficient estimate of skills intensity, *SVP*, is slightly lower than that of OLS (i.e., 0.0177 vs. 0.0117) but still statistically significant at the 1-percent level. This indicates that the skills intensity of the current occupation has a significant effect on the workers' own wages over time even after eliminating the unobserved heterogeneity.

Column (5) shows that the FE coefficient estimates of occupational investment and occupational investment^2 are 0.0130 and -0.0004. As we can see, the coefficient estimate of the linear term of occupational investment is statistically significant at the 1-percent level while that of the squared term is statistically insignificant. The F-test for the significance of both terms of occupational investment, however, indicates that they are highly jointly significant (F=83.05, p<0.0001). This emphasizes the role of occupational investment as one of the primary sources of variance in workers' own wages over time although the diminishing effect of occupational investment in this specification is not supported. Column (6) presents the FE coefficient estimates of occupational investment together with *SVP* on wages. The coefficient estimate of *SVP* is positive and still statistically significant at the 5-percent level. In particular, a 10-percent increase in *SVP* at the mean increases wages by about 6 percent.

Returning to Table 9, the upper part of the table compares the OLS and FE accumulated effects of the first two and five years of human capital measures. In particular, the first two and five years of occupational tenure, based on OLS, increase wages by 5.6 and 12.6 percent while the FE estimate drops to around 2.7 and 5.8 percent, respectively. The coefficient estimate of industry tenure is somewhat smaller than that of occupational tenure. The first two and five years of industry tenure, based on OLS, increase wages by 3.1 and 6.9 percent, while the first two and five years of industry tenure, based on FE, increase wages by 2.2 and 4.6 percent. The first two and five years of firm tenure, based on OLS, increase wages by 3.4 and 7.3 percent while the FE estimate drops to around 2.8 and 5.7 percent. Note that while the returns of tenures are important, they are not as large as the return to general labor market experience. The OLS return to two and five years of labor market experience are 10.3 and 24.6 percent while the FE return to 2 and 5 years of general labor market experience are 19.9 and 47.8 percent. This large increase in the FE return to labor market experience is probably from the strong correlation between labor market experience and other tenure measures, which implies that the upward bias in the tenure measures resulting from the unobserved heterogeneity will result in a downward bias in the experience estimates (Altonji and Shakotko, 1987). The lower part of Table 9 reports the cumulative effect of human capital, emphasizing occupational investment. As we can see, the return to occupational investment relative to two and five years of occupational tenure based on OLS is 7.3 and 16.3 percent, while the return to occupational investment based on FE drops by over 50 percent relative to the OLS to around 3.2 and 7.1 percent. As mentioned earlier, this large drop in the FE estimate is probably attributed to the bias from the positive correlation between occupational investment and unobserved heterogeneity that affects wages.

To compare the effect of occupational tenure with occupational investment on workers' wages, Table 9 also shows that the overall effect of the first five years of occupational tenure is to raise wages by 5.8 to 12.6 percent while the occupational investment results in a wage increase of 7.1 to 16.3 percent over the first five years. As we can see, the return to occupational investment is higher than that of occupational tenure, indicating the significant effect of occupational skills transferred from the previous occupation and current occupational skills on wages.

In summary, the OLS and FE estimates of the wage equation indicate the significant effect of the occupational skills transferability on wages. In particular, two additional years of occupational skills from the previous occupation, on average, increase the workers' wages by 1.2 to 2.4 percent controlling for the current occupational tenure, and the return to (3-digit) occupational investment relative to five years of occupational tenure is around 7.1 to 16.3 percent. Regarding other components of human capital, the OLS and FE estimates indicate that labor market experience increases wages by 10 to 20 percent during the first two years of work and 22 to 48 percent during the first five years; the firm tenure increases wages by 2 to 3 percent during the first two years of work and 5.5 to 7 percent during the first five years of work; the industry tenure increases wages by 2 to 3 percent during the first two years of work and 4 to 7 percent during the first five years. As we can see, the large reduction in the tenure estimates is accompanied by a large offsetting increase in the labor market experience. This is expected because the fairly strong and positive correlation between labor market experience and tenure measures, shown in Table 7, implies that the upward bias in the tenure estimates resulting from unobserved heterogeneity will result in a downward bias in the OLS estimate of labor market experience. The wage rising with the labor market experience could come from the general skills accumulation over time or from the labor market search (Altonji and Shakotko, 1987).

5.4 Comparison of Shaw's and Ormiston's Skills Transferability

Table 11 reports the comparison of the OLS coefficient estimates of Shaw's and Ormiston's skills transferability at the 2-digit level. Column (1) and (3) show that the coefficient estimate of Ormiston's skills transferability is 0.0057, and it is statistically significant at the 5-percent level, while the Shaw's skills transferability estimate is negative and statistically insignificant. This implies that the Shaw's skills transferability estimate at the 2-digit level does not contribute to wages across workers after controlling for the current occupational tenure.

Column (2) shows that the linear estimate of occupational investment based on Ormiston's approach is 0.0280 and it is statistically significant at the 1-percent level while the squared term of occupational investment is -0.0007, and it is statistically significant at the 10-percent level. Column (4) shows that the coefficient estimates of occupational investment based on Shaw's approach are 0.0311 and -0.0011, and they are statistically significant at the 5-percent level. This indicates that although the Shaw's skills transferability in itself, on average, does not contribute to wages across workers, the total occupational investment still has a significant effect on wages.

Table 12 reports the comparison of the FE estimates of Shaw's and Ormiston's occupational skills transferability at the 2-digit level. In contrast to the OLS estimates in Table 11, the FE estimates of both Shaw's and Ormiston's skills transferability are negative and statistically insignificant, indicating that occupational skills from the previous occupation might not contribute to the workers' own wages over time. On the other hand, Column (2) shows that the linear estimate of occupational investment based on Ormiston's approach is 0.0116 and it is statistically significant at the 1-percent level while the squared term of occupational investment is -0.0004, and it is statistically significant at the 10-percent level. Column (4) shows that the coefficient estimates of occupational investment based on Shaw's approach are 0.0155 and -0.0007, and they are statistically significant at the 5-percent level. Although the coefficients of occupational investment relatively drop compared to the OLS estimate, the occupational investment estimates from both methods are statistically significant.

Table 13 reports the results including both Shaw's and Ormiston's occupational investments into the same equation. Column (2) presents the OLS result. On the one hand, the F-test for the significance of Ormiston's occupational investment (both linear and quadratic forms) indicates the non-statistical significance (F=1.25, p=0.28), which implies that Ormiston's occupational investment does not add information into the model once controlling for Shaw's occupational investment. On the other hand, the F-test for the significance of Shaw's occupational investment (both linear and quadratic forms) indicates that they are highly jointly significant ($F=16.66$, $p<0.0001$), which implies that Shaw's occupational investment adds information to the model of Ormiston's occupational investment. Column (5) presents the FE result. The F-test for the significance of Ormiston's and Shaw's occupational investments indicate that both types of skills transferability are jointly significant to each other ($F=4.6$, $p=0.01$ and $F=12.07$, $p<0.0001$, respectively).

Table 14 reports the overall effect of the first two and five years of Ormiston's and Shaw's occupational investment. In particular, the OLS return of occupational investment relative to the first two and five years of occupational tenure based on Ormiston's method are 7.09 and 15.81 percent, while the FE return to the first two and five years drops to around 2.84 and 6.13 percent. Similarly, the OLS return to the first two and five years of occupational investment based on Shaw's method are 6.03 and 13.33 percent while the FE return to the first two and five years drops to around 2.90 and 6.19 percent. As we can see, both approaches produce a fairly similar effect on workers' wages.

6. Conclusion and Future Research

Most previous studies of the labor market assume that skills are either completely general (e.g., years of education and labor market experience) or specific to a particular firm (e.g., firm tenure). Recent studies, however, suggest that skills might be specific to occupation, and they are more likely to be an important source of wage determination. In this chapter, I apply Shaw's (1984) concept of occupational human capital to create a measure of occupational investment incorporating skills transferability as a proxy for occupational human capital. The key findings of this chapter suggest that the occupational skills from previous jobs can also affect the workers' wages at the current job and that the occupational investment measure is one of the important determinants of workers' wages over the lifecycle. In particular, controlling for the tenure at the current occupation, two years of occupational skills transferred from the previous occupation, on average, increase wages by 1.0 to 2.6 percent, and the return to occupational investment relative to the first five years of occupational tenure at the 3-digit level is around 7.1 to 16.3 percent. Since the (3-digit) occupational skills transferability is statistically significant based on both OLS and FE, it implies that occupational skills transferability not only helps to explain differences in wages across workers (relative wages) but also is necessary for the wage growth of the worker as well. In addition, the finding shows that the occupational skills intensity at the current occupation is also important for determining the workers' wages. In particular, a 10-percent increase in *SVP* at the mean increases current wages by about 6 to 9 percent. Moreover, consistent with Altonji and Shakotko's (1987), I also find that general labor market experience accounts for a large share of wages. This indicates the importance of general skills accumulation, which is emphasized in human capital theory, and the labor market search, which is emphasized in the search model (Altonji and Shakotko, 1987).

One of the limitations of this study comes from the possibility of an additional endogeneity problem. FE estimation does not eliminate all of the potential biases created by the correlation between tenure variables and the error term in the wage equation. In particular, FE only eliminates the bias from the unobserved factors that are constant over time. However, there are still other unobserved factors, such as the job quality match, that are not constant over time, and they are likely to be correlated with the tenure measures and wages. It is possible that a worker could get into a “good” firm that always pays higher wages, so he/she is more likely to stay in that firm longer. If this is the case, then the FE-estimated coefficients on firm tenure would be biased up. Since the firm tenure is positively and highly correlated with other tenure measures, the FE estimates of other tenures, including occupational tenure and occupational investment, would be biased down. In other words, the estimated coefficients of occupational tenure and investment would be the lower bound of the true effect of occupational human capital.

While not without limitation, the findings in this chapter significantly enhance our understanding of the importance of occupational human capital and skills transferability in wage determination. My results suggest that the occupational investment is one of the key sources of variation in wages.

For the future research, the concept of occupational human capital is relevant for studies of wage inequality (e.g., gender wage gap, or racial wage disparities). Specifically, the gender wage gap literature considers the role of post-school human capital investment operationalized as accumulation of general skills (years of market experience), the returns to firm tenure, and the return to job shopping over the career. However, there has been no research that directly incorporates the idea of occupational human capital into the gender wage differences. It is well known that men and women are concentrated in different occupations throughout the labor force and have different patterns of lifecycle labor supply. Thus, in future research, I can also examine differences in patterns of occupational change and skills transferability as well as skills intensity by gender and the extent to which these differences contribute to the gender wage gap.

Similarly, the idea of occupational human capital could apply to a study of the public and private wage differentials. The U.S. labor force studies generally indicate that public workers’ earnings, on average, are higher than private workers’ earnings. While the private workers’ pay and benefits have stagnated, public workers' compensation advantage has grown from $30,415 in 2000 to $61,998 in 2009, which is more than double what private sector workers earn (Cauchon, 2010). The clarification for the existence of these wage differences is still a puzzle. There are multiple factors proposed to explain the likelihood of positive public wage differentials. One explanation emanates from the difference in union bargaining power. Belman et al. (1997) contend that public sector unions may have a greater ability than private sector unions to raise their relative wage rates because of the relatively low elasticity of demand for labor in the public sector. Another explanation comes from the segmented labor market model. The recent evidence shows that the distribution of workers across occupations shared by public and private sectors are very different (Belman and Heywood, 2004). Those occupations in the public sectors are much more educated and more likely to be in professional or technical positions than those in the private sector. Despite taking into account those above factors, there is still a significant residual to be explained. In particular, there is relatively little research examining the role of occupational human capital. The public wage premium might exist because of the lower relative occupational mobility or higher skills transferability of the public sector labor workforce, which in turn will contribute to higher earnings.

Also, future research may benefit from the application of occupational skills transferability measure to the modeling of other outcome variables as well. For example, this paper only examines the effect of occupational skills transferability on wages and does not consider the effect on other types of benefits. Thus, it might be interesting for the future research to investigate the effect of occupational human capital, especially the skills transferability, on total compensation, which also includes other benefits such as the health insurance and pension (Podgursky and Swaim, 1987).

Figure 1. Occupational Changes among Employed Workers at the 1-, 2-, and 3-digit Occupations from 1979–2000

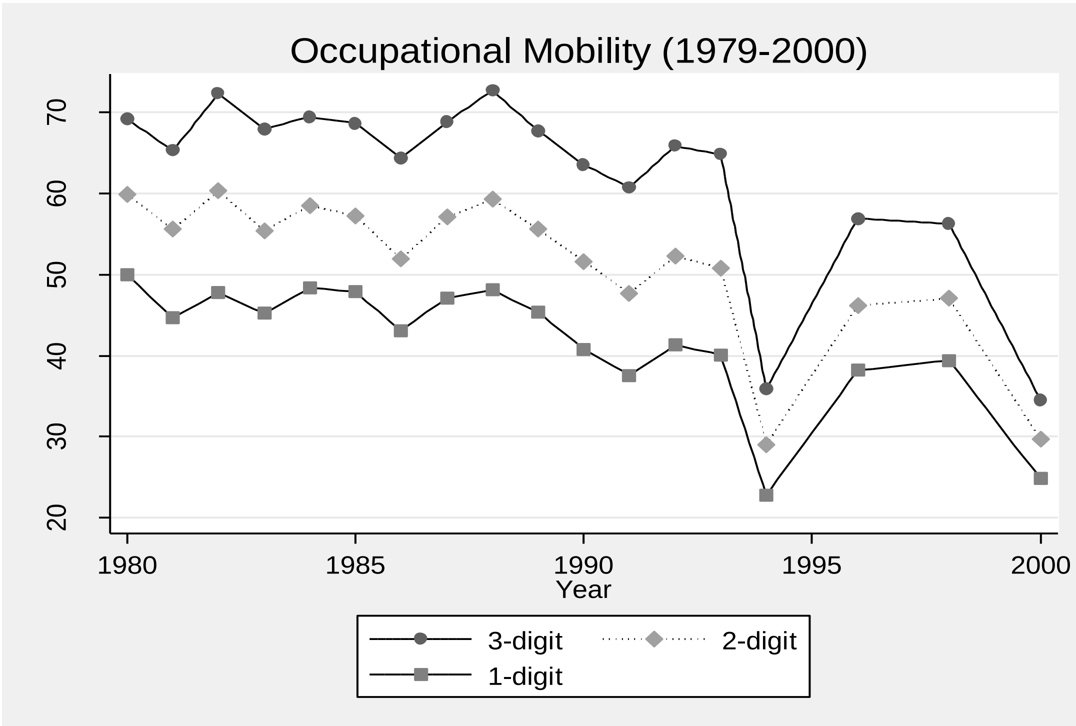

Table 6. Descriptive Statistics of Key Variables (1979–2000)

Variable	Mean	Std. Dev.
Real hourly wage ($1979)	5.70	3.61
Age	27.43	5.82
Education	12.22	2.31
Occupation tenure (3-digit)	2.45	2.46
Occupation tenure (2-digit)	3.19	3.11
Occupational investment (3-digit)	3.29	2.80
Occupational investment (2-digit, Shaw's approach)	3.30	3.12
Occupational investment (2-digit, Ormiston's approach)	4.27	3.42
Industry tenure (3-digit)	3.40	3.49
Industry tenure (2-digit)	3.96	3.85
Firm tenure	3.41	3.91
Experience	8.12	5.33
SVP	5.14	1.71
Number of firms changed	3.71	2.57
Number of Observations	26,818	
Number of Individuals	2,309	

Table 7. Correlations among Key Human Capital Measures

	Experience	Firm tenure	Industry tenure	Occupational tenure	Occupational investment
Experience	1.000				
Firm tenure	0.559	1.000			
Industry tenure	0.633	0.603	1.000		
Occupational tenure	0.579	0.465	0.581	1.000	
Occupational investment	0.687	0.524	0.640	0.922	1.000

Table 8. OLS Estimates of the Wage Equation

Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Experience (in years)	0.0567	0.0528	0.0510	0.0503	0.0513	0.0502	0.0491	0.0484
	(10.22)	(9.49)	(9.10)	(9.00)	(9.18)	(8.44)	(8.56)	(8.45)
Experience^2	-0.0008	-0.0007	-0.0007	-0.0007	-0.0007	-0.0007	-0.0007	-0.0007
	(-3.71)	(-3.55)	(-3.49)	(-3.38)	(-3.55)	(-2.99)	(-3.13)	(-3.03)
Firm tenure (in years)	0.0207	0.0183	0.0180	0.0178	0.0167	0.0178	0.0179	0.0177
	(5.92)	(5.29)	(5.16)	(5.09)	(4.79)	(4.64)	(5.12)	(5.06)
Firm tenure^2	-0.0008	-0.0007	-0.0007	-0.0007	-0.0006	-0.0007	-0.0007	-0.0007
	(-3.68)	(-3.33)	(-3.26)	(-3.21)	(-2.89)	(-2.66)	(-3.23)	(-3.19)
Industry tenure (in years)	0.0244	0.0170	0.0168	0.0167	0.0170	0.0165	0.0174	0.0173
	(6.79)	(4.73)	(4.66)	(4.64)	(4.72)	(4.26)	(4.85)	(4.83)
Industry tenure^2	-0.0009	-0.0007	-0.0007	-0.0007	-0.0007	-0.0007	-0.0007	-0.0007
	(-3.73)	(-2.88)	(-2.97)	(-2.96)	(-3.05)	(-2.7)	(-3.11)	(-3.1)
Occupation tenure (in years)		0.0299	0.0311	0.0306	0.0307	0.0281		
		(7.04)	(7.15)	(7.04)	(7.05)	(5.88)		
Occupation tenure^2		-0.0009	-0.0009	-0.0009	-0.0009	-0.0006		
		(-2.32)	(-2.24)	(-2.2)	(-2.19)	(-1.33)		
Occupational transferability			0.0127	0.0118	0.0120	0.0095		
			(3.06)	(2.84)	(2.85)	(2.21)		
Occupational investment							0.0291	0.0286
							(6.31)	(6.19)
Occupational investment^2							-0.0007	-0.0007
							(-1.98)	(-1.95)
SVP				0.0177				0.0175
				(3.91)				(3.85)
TQ					0.0294			
					(4.96)			
JobZone						0.0459		
						(5.70)		
#Observations	26,818	26,818	26,818	26,818	26,515	23,041	26,818	26,818
Adj. R^2	0.4013	0.4064	0.4069	0.4076	0.4067	0.4168	0.4067	0.4074

Note: t-statistics are in the parentheses. Not included independent variables are years of education, age, marital status, major occupation and industry dummies, SMSA, year dummies, region dummies, and a dummy variable indicating whether an individual works for a current firm more than one year.

Table 9. Cumulative Returns to Human Capital Measures

Variable	OLS		FE	
	Column(2) of Table 8		Column(3) of Table 10	
	2 years	5 years	2 years	5 years
Firm tenure	0.034	0.073	0.028	0.057
	(0.008)	(0.023)	(0.006)	(0.018)
Occupational tenure	0.056	0.126	0.027	0.058
	(0.010)	(0.031)	(0.008)	(0.024)
Industry tenure	0.031	0.069	0.022	0.046
	(0.008)	(0.024)	(0.006)	(0.019)
Total experience	0.103	0.246	0.199	0.478
	(0.012)	(0.033)	(0.016)	(0.042)
	Column(7) of Table 8		Column(5) of Table 10	
	2 years	5 years	2 years	5 years
Firm tenure	0.033	0.071	0.028	0.056
	(0.008)	(0.023)	(0.006)	(0.018)
Occupational investment*	0.073	0.163	0.032	0.071
	(0.015)	(0.047)	(0.011)	(0.036)
Industry tenure	0.032	0.069	0.023	0.048
	(0.008)	(0.024)	(0.006)	(0.019)
Total experience	0.096	0.229	0.195	0.468
	(0.012)	(0.034)	(0.016)	(0.043)

Note: standard deviations are in the parentheses.
* The return to occupational investment is calculated by using the relative number of current occupational tenures and the skills transferability.

Table 10. FE Estimates of the Wage Equation

Independent variable	(1)	(2)	(3)	(4)	(5)	(6)
Experience (in years)	0.1058	0.1021	0.1006	0.1003	0.1000	0.0996
	(14.24)	(13.77)	(13.53)	(13.48)	(13.37)	(13.33)
Experience^2	-0.0014	-0.0013	-0.0013	-0.0013	-0.0013	-0.0013
	(-6.79)	(-6.45)	(-6.36)	(-6.31)	(-6.18)	(-6.13)
Firm tenure (in years)	0.0169	0.0160	0.0158	0.0156	0.0158	0.0157
	(6.14)	(5.79)	(5.72)	(5.65)	(5.72)	(5.66)
Firm tenure^2	-0.0010	-0.0009	-0.0009	-0.0009	-0.0009	-0.0009
	(-5.40)	(-5.22)	(-5.18)	(-5.11)	(-5.20)	(-5.13)
Industry tenure (in years)	0.0157	0.0125	0.0125	0.0124	0.0132	0.0132
	(5.64)	(4.53)	(4.50)	(4.47)	(4.77)	(4.76)
Industry tenure^2	-0.0008	-0.0007	-0.0007	-0.0007	-0.0007	-0.0007
	(-3.89)	(-3.38)	(-3.45)	(-3.46)	(-3.69)	(-3.71)
Occupation tenure (in years)		0.0148	0.0160	0.0159		
		(4.52)	(4.75)	(4.73)		
Occupation tenure^2		-0.0006	-0.0006	-0.0006		
		(-2.10)	(-2.12)	(-2.10)		
Occupational transferability			0.0059	0.0054		
			(1.92)	(1.77)		
Occupational investment					0.0130	0.0129
					(3.71)	(3.66)
Occupational investment^2					-0.0004	-0.0003
					(-1.31)	(-1.27)
SVP				0.0117		0.0115
				(3.48)		(3.43)
#Observations	26,818	26,818	26,818	26,818	26,818	26,818
Adj. R^2	0.3088	0.3100	0.3101	0.3101	0.3099	0.3104

Note: t-statistics are in the parentheses. Not included independent variables are years of education, age, marital status, major occupation and industry dummies, SMSA, year dummies, region dummies, and a dummy variable indicating whether an individual works for a current firm more than one year.

Table 11. Comparison of Shaw's and Ormiston's Skills Transferability (OLS)

	OLS			
	Ormiston's approach		Shaw's approach	
Independent Variable	(1)	(2)	(3)	(4)
Experience (in years)	0.0453	0.0418	0.0471	0.0456
	(12.12)	(10.73)	(12.62)	(12.29)
Experience^2	-0.0005	-0.0005	-0.0006	-0.0005
	(-3.45)	(-2.84)	(-3.53)	(-3.30)
Firm tenure (in years)	0.0158	0.0159	0.0160	0.0160
	(5.80)	(5.79)	(5.87)	(5.85)
Firm tenure^2	-0.0006	-0.0006	-0.0006	-0.0006
	(-3.57)	(-3.66)	(-3.56)	(-3.57)
Industry tenure (2-digit, in years)	0.0195	0.0418	0.0197	0.0196
	(7.50)	(10.73)	(7.55)	(7.52)
Industry tenure^2	-0.0008	-0.0005	-0.0008	-0.0008
	(-5.01)	(-2.84)	(-4.93)	(-4.93)
SVP	0.0180	0.0177	0.0182	0.0184
	(5.93)	(5.82)	(6.01)	(6.06)
Occupation tenure (2-digit, in years)	0.0311		0.0297	
	(11.10)		(10.72)	
$\text{Occupation tenure}^2$	-0.0010		-0.0010	
	(-5.31)		(-5.36)	
Occupational transferability	0.0057		-0.0174	
	(2.02)		(-1.09)	
Occupational investment		0.0280		0.0311
		(8.69)		(10.99)
$\text{Occupational investment}^2$		-0.0007		-0.0011
		(-3.61)		(-5.53)
#Observations	26,818	26,818	26,818	26,818
Adj. R^2	0.4084	0.4075	0.4084	0.4083

Note: t-statistics are in the parentheses. Not included independent variables are years of education, age, marital status, major occupation and industry dummies, SMSA, year dummies, region dummies, and a dummy variable indicating whether an individual works for a current firm more than one year.

Table 12. Comparison of Shaw's and Ormiston's Skills Transferability (FE)

	FE			
	Ormiston's approach		Shaw's approach	
Independent Variable	(1)	(2)	(3)	(4)
Experience (in years)	0.0982	0.0963	0.0987	0.0973
	(13.04)	(12.64)	(13.11)	(12.98)
Experience^2	-0.0012	-0.0012	-0.0012	-0.0012
	(-5.70)	(-5.37)	(-5.75)	(-5.60)
Firm tenure (in years)	0.0140	0.0142	0.0140	0.0140
	(5.04)	(5.09)	(5.04)	(5.03)
Firm tenure^2	-0.0008	-0.0008	-0.0008	-0.0008
	(-4.49)	(-4.60)	(-4.48)	(-4.50)
Industry tenure (2-digit, in years)	0.0151	0.0163	0.0150	0.0150
	(5.38)	(5.83)	(5.37)	(5.37)
Industry tenure^2	-0.0007	-0.0008	-0.0007	-0.0007
	(-4.02)	(-4.36)	(-4.01)	(-4.03)
SVP	0.0123	0.0120	0.0122	0.0124
	(3.68)	(3.57)	(3.65)	(3.68)
Occupation tenure (in years)	0.0147		0.0144	
	(5.13)		(5.17)	
$\text{Occupation tenure}^2$	-0.0006		-0.0006	
	(-3.09)		(-3.06)	
Occupational transferability	-0.0012		-0.0210	
	(-0.39)		(-1.01)	
Occupational investment		0.0116		0.0155
		(3.39)		(5.55)
$\text{Occupational investment}^2$		-0.0004		-0.0007
		(-1.67)		(-3.18)
#Observations	26,818	26,818	26,818	26,818
Adj. R^2	0.3113	0.3106	0.3114	0.3113

Note: t-statistics are in the parentheses. Not included independent variables are years of education, age, marital status, major occupation and industry dummies, SMSA, year dummies, region dummies, and a dummy variable indicating whether an individual works for a current firm more than one year.

Table 13. Comparison of Additional Information from Shaw's and Ormiston's Occupational Investment

Independent Variable	OLS (1)	(2)	(3)	FE (4)	(5)	(6)
Occupational investment (Shaw's)	0.0311	0.0276		0.0155	0.1029	
	(10.99)	(4.62)		(5.55)	(2.62)	
Occupational investment^2(Shaw's)	-0.0011	-0.0011		-0.0007	-0.0153	
	(-5.53)	(-2.32)		(-3.18)	(-4.49)	
Occupational investment (Ormiston's)		0.0037	0.0280		-0.0202	0.0116
		(0.53)	(8.69)		(-2.64)	(3.39)
Occupational investment^2(Ormiston's)		0.0001	-0.0007		0.0016	-0.0004
		(0.18)	(-3.61)		(3.03)	(-1.67)
#Observations	26,818	26,818	26,818	26,818	26,818	26,818
Adj. R^2	0.4083	0.4084	0.4075	0.3113	0.3119	0.3106

Note: t-statistics are in the parentheses. Not included independent variables are experience, firm tenure, industry tenure, years of education, age, marital status, major occupation and industry dummies, SMSA, year dummies, region dummies, and a dummy variable indicating whether an individual works for a current firm more than one year.

Table 14. Comparison of Cumulative Returns to Shaw's and Ormiston's Occupational Investment

Variable	OLS 2 years	OLS 5 years	FE 2 years	FE 5 years
Occupational investment (Ormiston) 2-digit	0.0709 (0.0101)	0.1580 (0.0305)	0.0284 (0.0107)	0.0613 (0.0326)
Occupational investment (Shaw) 2-digit	0.0603 (0.0067)	0.1333 (0.0199)	0.0290 (0.0067)	0.0619 (0.0201)

* The return to occupational investment is calculated by using the relative number of current occupational tenures and the skills transferability.

Chapter 3

OCCUPATIONAL HUMAN CAPITAL AND EARNINGS LOSSES OF DISPALCED WORKERS: DOES THE DEGREE OF SIMILARITY BETWEEN PRE- AND POST-DISPLACEMENT OCCUPATIONS MATTER?

1. Introduction

The costs of job displacement have received considerable attention from policy makers and researchers in previous decades. The recent recession and the resulting dramatic increase in involuntary displacement have increased interest in this issue. Millions of prime-age workers have been displaced, and those fortunate enough to find employment have often suffered substantial reductions in earnings. Studies of the U.S. labor force have indicated that displaced workers suffer a large and persistent loss of earnings (for example, Ruhm, 1991; Jacobson et al., 1993; Kletzer and Fairlie, 2003). Ruhm (1991) found that the weekly earnings of displaced workers were 16 percent lower than those of non-displaced workers one year following the displacement. Four years after displacement, their earnings remained 14 percent below their former earnings. Given the large and ongoing losses suffered by displaced workers, it is important to determine the factors affecting the magnitude of earnings losses associated with displacement.

The goal of this chapter is to investigate the effect of accumulated human capital, and particularly occupational human capital, on earnings losses. Specifically, to what extent does the similarity between pre- and post-displacement occupations affect the earnings losses of the displaced workers? I hypothesize the earnings losses associated with displacement are affected by the degree to which occupation-specific skills can be transferred across occupations. Among workers who switch occupations following displacement, I predict those who switch to a closer (more similar) occupation will suffer smaller earnings losses than those who switch into a dissimilar occupation, as they lose fewer of their occupation-specific skills. Unlike previous studies of job displacement, I use a continuous measure of occupational skills transferability based on Shaw's and Ormiston's approaches developed in Chapter 1 to measure the similarity between pre- and post-displacement occupations of reemployed displaced workers.

This chapter uses the data from the 2004, 2006, 2008, and 2010 Displaced Worker Survey (DWS) biennial supplement to the Current Population Survey (CPS) to estimate the portion of earnings losses attributable to lack of occupational skills transferability. This dataset contains the retrospective data on both pre- and post-displacement labor market circumstances, including occupations, for a large sample of workers who lost their jobs over the period of 2001 to 2009.

The main findings of this chapter show that post-displacement earnings losses are highly correlated with the degree of similarity between pre- and post-displacement occupations. Displaced workers who find jobs in occupations similar to their previous jobs, as measured by occupational skills transferability, suffer smaller earnings losses than those who find less similar jobs. For example, using Ormiston's measure, displaced workers whose new jobs measure 10 percentage points closer to their previous job on the occupational similarity measure experience approximately 4 percent less earnings losses. In addition, this relationship is non-linear: higher skills transferability reduces the earnings losses at a decreasing rate.

These findings provide important insight into the determination of earnings losses following job displacement. First, from a theoretical perspective, this research contributes to the human capital literature by emphasizing the importance of occupational human capital and the idea that occupational skills are (partially) transferable across occupations. From a policy perspective, it provides valuable guidance for the development of government programs to help displaced workers. For example, the Trade Adjustment Assistance (TAA) program provides trade-displaced workers with retraining, job-search assistance, a health care tax credit, and an additional period of unemployment benefits at a total cost of $2 billion annually (White, 2009; Baicker and Rehavi, 2004). The objective of job-search assistance is to help displaced workers return to work as soon as possible in order to increase their short-run earnings. In contrast, my results suggest that a focus on helping workers find occupations similar to their pre-displacement jobs may help reduce the earnings losses of displaced workers.

The structure of this chapter is as follows. Section 2 summarizes the literature on the role of human capital in earnings losses due to displacement. Section 3 sets up the methodological framework. Section 4 describes the main dataset and related variables. Section 5 discusses the descriptive statistics. Section 6 presents the main findings and robustness tests based on Ormiston's approach at the 3-digit level as well as the comparison of Shaw's and Ormiston's approaches at the 2-digit level. The last section concludes and discusses some of the implications for policy makers and for future research.

2. Literature Review

In general, a displaced worker is defined as someone who is involuntarily separated from his or her job as a consequence of economic factors and business decisions of the employer that are beyond the control of the workers. Those who lose jobs because of individual job performance or who decide to voluntarily quit are not considered displaced workers. Studies of the U.S. labor force generally agree that displaced workers earn less in their post-displacement occupations than their original jobs; however, they differ in their estimates of the amount of earnings losses and provide little insight into the sources of earnings losses. For example, Jacobson et al.(1993) used quarterly administrative data from the state of Pennsylvania and found that the displaced workers who are 20 years old or older suffered earnings losses of more than 40 percent one year following displacement. Six years later, their earnings were still reduced by 25 percent. Using the National Longitudinal Survey of Youth (NLSY), Kletzer and Fairlie (2003) found that young displaced male and female workers (19 to 27 years old) have lower earnings by approximately 9 percent five years after displacement. The differences in estimates across studies could be due to differences in the data used or the methodology, or the discrepancies could simply reflect unexplained variance in the earnings losses workers experience.

There are many factors in the previous literature that were proposed and tested empirically to explain the earnings losses of displaced workers, including human capital attributable to a job, unionization, job quality match, and local market conditions (Topel, 1991; Carrington, 1993; Kletzer, 1998). In this section, I review studies based on the human capital theory. The idea that human capital is an important determinant of earnings is not new. The human capital model proposed by Becker (1964) categorizes human capital skills into two types. Although these two types are widely known throughout the economics literature, it is useful for the purpose of defining occupational human capital to revisit these original distinctions. The first type of human capital in Becker's model is “general human capital,” which is defined as skills that are productive and completely transferable across different firms. The second is “firm specific human capital,” which is defined as skills that are productive (unique) at only one firm and not transferable across firms. Typically, workers acquire these specific skills through on-the-job training by the employer, familiarity with employers’ processes, production lines, or business culture. As the amount of skill increases with tenure at a given firm, earnings also rise. On the one hand, if human capital skills are “general” in the case of being transferable across firms, then the effect of displacement on earnings losses should be minor. On the other hand, if firm-specific skills are important for determining earnings, then workers with high levels of firm-specific skills who are displaced from their jobs are more likely to experience large and possibly persistent earnings losses (Kletzer, 1998). There is some empirical evidence to support the idea that workers with more specific human capital experience greater earnings losses. Most previous studies find that earnings following job displacement is strongly correlated with pre-displacement years of work experience and job tenure (for example, Podgursky and Swaim, 1987; Topel, 1990; Carrington, 1990; Faber, 1993). Faber (1993) used the Displaced Workers Survey (DWS) and found that each additional year of pre-displacement firm tenure is related to additional earnings losses of 1to1.3 percent. Using a different methodology, Topel (1991) found that when a worker with 10 years of tenure is displaced, post-displacement wages were approximately 25 percent lower.

More recent literature on job displacement has started to explore the importance of other dimensions of human capital and to emphasize that workers' earnings likely depend on skills that are not completely general or firm-specific but instead specific to the worker's industry or occupation. Several studies have found that some skills are transferable within but not between industries (for example, Podgursky and Swaim, 1987; Carrington, 1993; Neal, 1995). In particular, the post-displacement earnings of workers who change industries are lower than those who could find a new job in the same industry. For example, Neal (1994) found that displaced workers who switch between 1-digit industries following displacement, on average, suffer greater wage losses than those who find new jobs in their pre-displacement industry. In addition, the post-displacement wages among displaced workers who stay in their old industry increase more sharply with pre-displacement tenure and years of labor market experience than among those who switch industries. In a related study, Carrington and Zaman (1994) found that there is inter-industry variation in the costs of job displacement. For instance, their results indicated that workers who were displaced from the manufacturing and mining industries, on average, suffered greater wage losses than those who were displaced in the service industry.

There are also several studies that have considered the importance of occupational human capital in explaining earnings losses (Carrington, 1990; Topel, 1990; Kambourov and Manovskii, 2009). For example, Topel (1990) used the Panel Study of Income Dynamics (PSID) from 1968 to 1985 and found that the workers who changed 1-digit occupations after displacement had a short-run reduction in annual earnings of approximately 17.2 percent during the first two years after displacement, while displaced workers who changed between 1-digit industries experienced only a 7 percent reduction in annual earnings. In addition, Kambourov and Manovskii (2009) demonstrated that:

> "On average, a currently employed worker who was displaced from a job in the preceding 5 years suffers 15 percent reduction in weekly earnings. However, those who stay in the same occupation after the displacement only suffer 6 percent drop in their weekly earnings, even after controlling for the pre-displacement firm tenure whereas those who switch their occupation experience an 18 percent drop." (pg. 63)

Thus, there is a growing body of evidence that some human capital is specific to occupation and industry. These empirical results are taken as evidence to support the idea that displaced workers who regain employment in the same occupation or industry are more likely to continue using more of their human capital, as so suffer lower earnings losses.

The aforementioned studies usually characterize occupations or industries upon reemployment as either "the same" or "different," generally using a dichotomous variable and either the 1-, 2- or 3-digit level industrial or occupational classifications. This approach inherently assumes that workers who could not find a job in their previous occupational or industrial category will lose all of their occupation- or industry-specific skills. However, in reality, at least some skills are likely to be transferred across occupations. For example, an engineer who is displaced from his old job and gets a new job as a clerk should be able to apply some portion of his engineering skills to a clerical job.

The idea of occupational skills transferability was first introduced by Shaw (1984). She defined the concept of occupational human capital as "individual investment in skills which relates to one particular occupation, and he/she would be able to transfer a certain amount of his/her occupation skills during the occupational switch depending on the "transferability" between those two occupations" (pg. 320–321). Ormiston (2006) later developed an occupational skills transferability index and showed that there is a positive relationship between skills transferability and occupational movement as well as post-displacement earnings among blue-collar workers.[12] In particular, he found that displaced blue-collar workers are more likely to choose a new occupation with high skills transferability. Building on Shaw's definition and the above findings, I apply the idea that skills specific to a given occupation are transferable to similar occupations but have limited transferability to dissimilar occupations. Therefore, workers should experience less (more) earnings losses when reemployed in occupations that is more (less) similar to their old jobs.

[12] His study mainly focuses on blue-collar occupations that include: transportation and material moving; production; installation, maintenance, and repair; construction and extraction; and farming, fishing, and forestry.

3. Empirical Methodology

As a first approximation, this chapter assumes that workers in the sample were exogenously displaced, and then a subset of them was randomly assigned to a new job. Of those who end up in a new job, I assume some are in occupations that are similar to the pre-displacement occupation, and others are not.[13] If these assumptions are true, then ordinary least square (OLS) regression will provide unbiased and consistent estimators. Equation 3.1 is the baseline specification for estimating the impact of occupational similarity on earnings losses.

$$\Delta \ln W_i = \beta_0 + \beta_1 Transfer_{i,lc} + \gamma' X_i + \varepsilon_i \qquad (3.1)$$

$\Delta \ln W_i$ is the difference in the natural logarithm of real weekly earnings between pre- and post-displacement jobs for individual i,[14] and negative values of this variable indicate larger earnings losses. $Transfer_{i,lc}$ is the skills transferability between pre- and post-displacement occupations (i.e., from occupation l to occupation c) at both 2- and 3-digit levels.[15] X_i is a vector of control variables including age, gender, marital status, race, years of tenure at the lost job, and other worker characteristics and work history variables (see Appendix Table D1 for a complete summary of all independent variables). Studies in this literature often control for labor market experience using the proxy variable *potential experience* (age-education-six) since the DWS lacks the measure of an actual year of market experience. However, given the change in the measure of education in the DWS after the 1992 survey from an actual number of years of

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[13] However, these workers might not represent a random sample of displaced workers because the probability of being displaced may differ across occupations.

[14] The real weekly earnings are measured in $2010. Also, since the dependent variable is in the log form, the estimated coefficients could be interpreted as percentage changes in earnings losses due to the job displacement.

[15] As described earlier, Ormiston's skills transferability is estimated at both the 2- and 3-digit levels while Shaw's skills transferability is estimated only at the 2-digit level.

education to education level, I opt for using worker age and education level instead. In addition, I include the unemployment rate during the year of the survey across states and a dichotomous variable indicating the year of displacement as proxies for labor market conditions that could affect the opportunities for displaced workers to find new jobs.[16] ε_i is an error term with mean zero and constant variance, and it is assumed to be independent and identically distributed across individuals.

Thus, β_1 in Equation 3.1 is the estimated effect of skills transferability between pre- and post-displacement occupations on earnings losses. If the transferability of occupational skills is important for determining the earnings losses, post-displacement earnings should be higher for reemployed workers who find occupations more similar to their old jobs. This means β_1 is anticipated to be positive.

Even if greater occupational similarity does reduce earnings losses on average, there is reason to expect diminishing returns to similarity. Specifically, the return to one additional percentage point of skills transferability will be higher for displaced workers who find post-displaced employment in an occupation with a low value of skills transferability (i.e. in a very dissimilar occupation) than those who have already found a closer match. To test this hypothesis, I estimate the following model:

$$\Delta \ln W_i = \beta_0 + \beta_1 Transfer_{i,lc} + \beta_2 Transfer^2_{i,lc} + \gamma' X_i + \varepsilon_i \qquad (3.2)$$

In particular, if the above hypothesis is correct, β_2 should be negative.

[16] Carrington (1993) introduced more diverse measures of local market conditions for pre-displacement occupations and industry markets for workers, and he found that these local market conditions can also explain some of the wage losses encountered by displaced workers.

Next, I compare the contribution of the skills transferability measure (i.e., a continuous variable bounded between 0 and 1) to the dichotomous occupational change measure commonly used in previous studies of occupational human capital. The dichotomous measure is equal to 1 if an individual changes occupations and 0 otherwise. I hypothesize that the continuous measure of occupational skills transferability will add information to the model and explain more of the variation in earnings losses than the dichotomous measure. To test this hypothesis, I estimate the following regressions:

$$\Delta \ln W_i = \beta_0 + \delta_1 SAMEOCC_i + \gamma' X_i + \varepsilon_i \qquad (3.3)$$

$$\Delta \ln W_i = \beta_0 + \beta_1 Transfer_{i,lc} + \beta_2 Transfer^2_{i,lc} + \delta_1 SAMEOCC_i + \gamma' X_i + \varepsilon_i \qquad (3.4)$$

According to the above hypothesis, one would expect that the inclusion of skills transferability ($Transfer_{i,lc}$ and $Transfer^2_{i,lc}$) in Equation 3.4 would decrease the magnitude of the coefficient on the dichotomous measure ($SAMEOCC_i$) as compared to the estimate from Equation 3.3. In addition, the adjusted R^2 of Equation 3.3 should be lower than that of Equation 3.2.

The preceding analysis relies on the two key assumptions laid out at the beginning of this section: (1) workers are exogenously displaced and (2) a random subset of workers is (randomly) assigned to new jobs. If these assumptions do not hold, the magnitudes of the estimated coefficients from the OLS regression might be misleading because of the selection bias. In particular, the sample in this analysis only includes displaced workers who had become reemployed by the time of the survey. Therefore, the estimated relationship between the skills transferability across occupations and earnings losses in this sample may be quite different from the relationship observed in the labor force as a whole, which includes both reemployed workers and workers who remain unemployed. To account for possible selection bias, I will use two methods. First, I use the sample restriction suggested in Neal's (1995) study, and second, I will use the Heckman selection correction method. The details and advantages and disadvantages of each strategy are discussed along with the results.

4. Data

To examine the effect of the transferability of occupational human capital skills on earnings losses following job displacement, I used the 2004, 2006, 2008, and 2010 Displaced Workers Survey (DWS), which is a supplement to the January Current Population Survey (CPS).[17] The DWS has been widely used in studies of displaced workers because of the comprehensiveness of its questions about the incidence and cost of job displacement. In particular, displaced workers in the DWS are identified based on a question in the CPS that asks, "During the last three calendar years, did you lose a job or leave one because: 1) the plant or company is closed or moved, 2) your position or shift is abolished, or 3) there is insufficient work?" If the answer from the respondent is "yes," they will be asked a series of questions regarding the lost job and current job (if they have been reemployed during the current survey).[18] Since each survey year collects information on job loss that includes three years of job displacement prior to the survey date, all four surveys provide information about workers who lost their jobs from 2001 (for the 2004 survey) to 2009 (for the 2010 survey).

[17] The data is publicly available at Center for Economic and Policy Research. 2011. CPS Displaced Worker Uniform Extracts, Version 1.02. Washington, DC (http://www.ceprdata.org/cps/dws_prog.php).

[18] If more than one job was lost during the pre-displacement period, information was obtained from the job held for the longest time.

One disadvantage of this dataset is that it is cross-sectional, which means that all pre-displacement job information is gathered through retrospective questions in the DWS. Retrospective data is subject to “recall bias.” In general, recall bias arises from the fact that people usually forget things that happened in the past. Studies suggest that a person’s memory decays exponentially with time and that people are more likely to remember more important events from the past (Evans and Leighton, 1995). For the DWS, displaced workers are asked to recall job history information over the past three years. This raises concerns that respondents may either understate or overstate the effects of job displacement.[19] However, a major advantage of this dataset, particularly when compared to other datasets such as the NLSY and PSID, is that it is a very large dataset drawn on a random sample of over 60,000 households. It is weighted to be representative of the U.S. population, and the measures in the dataset are straightforward (Kletzer, 1998). In addition, the three-year interval of information collected on job displacement in the DWS also provides the data to determine variations in the amount of time since displacement at the time of interview (Carrington, 1990).

The DWS provides pre- and post-displacement 2- and 3-digit U.S. census occupation codes and weekly earnings that I used in my regression analysis. Specifically, the pre- and post-displacement 2- and 3-digit occupations are compared to attach the value of skills transferability. The sample in this analysis includes individuals who are between the ages of 20 and 62 who were reemployed at the time of the survey.[20] There were 27,540 displaced between 2001 and 2006. Of those displaced workers, 20,713 were excluded from this sample because they were not

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[19] For a more careful discussion about the recall bias of DWS, see Evans and Leighton (1995), and Kletzer (1998).

[20] The typical reason to exclude workers aged above 62 because these workers will, in general, be qualified for the social security retirement payments and therefore might encounter the different set of constraints in the labor marker than the younger workers (Podgursky and Swaim, 1987).

reemployed by the time of survey, or they did not supply data on the key variables such as pre- and post-displacement occupations. I also excluded displaced workers who served in the military or were self-employed for either pre- or post-displacement jobs.[21] My final sample, therefore, consists of 6,827 individuals.

5. Descriptive Statistics

Appendix Table D1 presents the summary statistics of the variables used in this analysis for the full sample pooling across the 2004 to 2010 surveys. The first row of Appendix Table D1 shows the mean changes in real weekly earnings (in $2010) between pre- and post-displacement jobs. On average, displaced workers earned 21 percent less when reemployed than in their pre-displacement job. The 21 percent translates to around a $121 loss in weekly earnings. The typical employee had worked for their former employer for five years, and 89.5 percent of workers in the sample worked full-time at the lost job. Educational attainment is divided into five categories: less than high school, high school, some college, college, and advanced degree. One third of the workers in the sample had a high school diploma, while another third had completed some college education. A majority of workers in this sample were white and relatively old (around 40 years old). Sixty percent of the sample received health insurance from their former employer and 43 percent qualified for unemployment insurance benefits. Appendix Table D2 presents descriptive statistics of these displaced workers compared to that of the full workforce from the CPS. To examine the implications of sample exclusion criteria, I compared the analysis sample to the full sample of workers in the CPS. With the exception of average weekly earnings, the workers in the displaced workers sample did not differ greatly from the full labor force. While

[21] The reason to exclude self-employed workers, especially at the pre-displacement job is because it is difficult to see how the idea of an exogenous displacement could be applied to self-employed workers.

the average weekly earnings at the current job of displaced workers were substantially lower for displaced workers than the full workforce (i.e., $685.01 vs. $789.89), the differences in gender, race, and age were quite small between the two samples.

Table 15 presents the proportion of reemployed workers who were displaced between 1991 and 2009 and found a different (3-digit) occupation from their previous job. Most displaced workers who were reemployed at the survey date (from 1994 to 2010) could not find the same 3-digit occupation in reemployment. Close to 70 percent of the reemployed workers ended up working in a different occupation from their old job.

Next, Figure 2 displays the distribution of occupational skills transferability among reemployed displaced workers. In particular, it shows that there is substantial variation in skills transferability. The average skills transferability is around 75 percent, which means that displaced workers, on average, found a job to which they could transfer 75 percent of their previous occupational skills.

To determine the relationship between earnings losses and the similarity between pre- and post-displacement occupations, measured by skills transferability, Figure 3 presents the average changes in the natural logarithm of real weekly earnings (in $2010) by the level of Ormiston’s skills transferability at the 3-digit level. Although the mean loss resulting from job displacement for the full sample is approximately 21 percent, Figure 3 shows that there is a wide dispersion across different levels of skills transferability. It indicates a positive relationship between occupational skills transferability (at the 3-digit level) and the decline of earnings losses. In particular, it shows that higher skills transferability from the previous occupation to the new occupation can help reduce earnings losses due to job displacement. For example, at a skills transferability level between 0.2 and 0.3 points, the average earnings losses were approximately

26 percent; at skills transferability between 0.3 and 0.4, they are around 21 percent. In addition, Figure 3 illustrates that as the skills transferability increased, the slope of earnings losses became flatter, illustrating the possibility of a non-linear relationship between skills transferability and earnings losses. Thus, Figure 3 provides descriptive evidence to support the hypotheses outlined above, and they motivate the idea of assessing the importance of occupational human capital and inter-occupational variation as a determinant of earnings losses as a result of job displacement.

6. Estimation Results

6.1 OLS Regression Results

While Figure 3 suggests that the ability to transfer occupational skills to a new job can reduce earnings losses following job displacement, the relationship may change when I control for observable characteristics. The empirical results based on Ormiston's skills transferability at the 3-digit level from the OLS regression shown in Table 16 highlight the effects of key independent variables on earnings losses of displaced workers. The parameter of interest is the coefficient on the transferability of occupational human capital ($Transfer_{i,lc}$).[22]

Column (1) of Table 16 is the standard model of occupational human capital and earnings losses, and it is similar to those used by prior studies. In this model, occupational human capital is captured by a dichotomous variable indicating whether the displaced worker remained at the same 3-digit occupation ($SAMEOCC_i$). This estimated coefficient represents the effect of occupation-specific human capital on earnings losses if workers lose all occupation-specific skills when displaced and reemployed in a new occupation. Consistent with the previous studies,

[22] The results in Table 15 are unweighted. I also apply the weighted regression using the CPS final sampling weights, and the results do not differ importantly from those shown in Table 15.

the regression result suggests that, on average, staying at the same 3-digit occupation reduces earnings losses by 10.50 percent, all else equal. In addition, staying at the same 3-digit industry also reduces earnings loss by 8.30 percent, all else equal.[23] The expected earnings loss of displaced workers who stay in their occupation and industry at the sample mean of worker characteristics is approximately 8.04 percent; the expected earnings loss of workers who only stay in their industry but change occupation is approximately 18.52 percent; the expected earnings loss of workers who only stay in their occupation but change industry is approximately 16.38 percent, and the expected earnings loss of workers who are displaced from both occupation and industry is approximately 26.86 percent. This implies that skills that are specific to occupation and industry are important to the determination of earnings losses.

In column (2), I substitute the skills transferability ($Transfer_{i,lc}$)—the continuous measure of occupational human capital which ranges from 0 to 1—for the dichotomous variable of switching occupations ($SAMEOCC_i$) to ascertain the effect of the skills transferability across occupations. There is a very strong association between occupational skills transferability and earnings losses. In particular, estimates suggest a 10 percentage points increase in skills transferability is associated with a 3.6 percent reduction in real weekly earnings holding other factors fixed, and the estimated coefficient is statistically significant at the 1 percent level. Also, the magnitude of the coefficient on the dichotomous industry change variable is reduced to 6.40 percent. Thus, this finding indicates a positive and strong relationship between the decline of earnings losses and occupational matches after job displacement. For example, consider the estimated earnings losses of two displaced workers, both of whom worked as HR managers. One

[23] The adjusted R^2 and estimated coefficients of other variables in the model are also consistent with the previous studies.

finds a new job as a sales manager, and the other becomes a baker. The skills transferability from the HR manager position to the sales manager position is equal to 0.8661 (86.61 percent of the HR skills transferred to the sales manager position), and the skills transferability from the HR manager position to the baker occupation is equal to 0.1593 (15.93 percent of the HR skills transferred to the baker occupation). According to these estimates, the expected earnings loss due to the loss of skills transferability of the worker who was displaced from the HR manager and reemployed as the sales manager was lower than the expected earnings loss of the other, who switched from the HR manager position to the baker occupation, by 28.0 percentage points.

In addition to the effect of occupational skills transferability, there is also a strong relationship between pre-displacement work history and subsequent earnings losses. For example, the coefficient of firm tenure at the lost job is negative and statistically significant. This highlights the importance of specialized skills that accumulate over time within a firm and are lost when changing jobs. Specifically, two additional years of tenure at a previous firm, on average, increased earnings losses by 1.60 percent, holding other variables fixed. This finding is consistent with other studies of the importance of firm-specific human capital that have found workers will lose all the skills specific to a particular firm when they change to a new employer (Podgursky and Swaim, 1987; Carrington, 1990;Topel, 1990).

The coefficient on individual workers' union membership at a pre-displacement job is negative and statistically significant at 1 percent level, indicating that unionized workers suffer larger earnings losses than the nonunionized workers. This is consistent with Khun and Sweetman's (1999) study, which also found a strong relationship between post-displacement earnings losses and union status. The earnings losses of displaced workers who collected unemployment insurance benefits were significantly greater than those who did not collect the benefit by 4.50 percent, all else equal. Also, displaced workers whose UI benefit had already been exhausted suffer greater earnings losses than those whose benefit was still available.

The coefficients of the remaining independent variables have the expected signs. For example, displaced workers working full-time at the lost job were more likely to suffer greater earnings decline by 31.40 percent relative to what they earned before they were displaced. The earnings losses of workers who were informed in advance about their job displacement were not statistically significant from those who were not informed in advance. Also, as mentioned above, we use *age* (and age^2) together with the education level as a proxy for the number of years of market experience. The coefficients of both *age* and age^2 are statistically significant at the 5 percent level, which implies that the number of years of general market experience, on average, help lower the earnings losses.

As indicated in Figure 3, the relationship between the occupational skills transferability and earnings losses might not be linear. Column (3), therefore, represents the results from Equation 3.4, which includes the quadratic form of skills transferability ($Transfer^2_{i,lc}$). The results show that both linear and quadratic terms of skills transferability are individually statistically significant at the 5 percent level. The F-test for the significance of both linear and quadratic forms of skills transferability indicates that these two variables are highly jointly significant ($F=15.84$, $p<0.0001$). In addition, the quadratic term has a negative value, implying that skills transferability reduces earnings losses at a decreasing rate.

Following Equation 3.3, column (4) includes both types of measures of occupational human capital (i.e., $Transfer_{i,lc}$, $Transfer^2_{i,lc}$ and $SAMEOCC_i$). The results show that when skills transferability ($Transfer_{i,lc}$ and $Transfer^2_{i,lc}$) is included in the model together with the dichotomous variable indicating switching occupations (*$SAMEOCC_i$*), the coefficient of *$SAMEOCC_i$* drops from 0.105 to -0.004 and becomes statistically insignificant while the magnitude of linear coefficient of skills transferability is still large and statistically significant at the 5 percent level. Compared with the standard model in column (1), the adjusted R^2 increases from 7.78 percent to 8.49 percent in column (4), indicating that skills transferability captures a slightly greater variation in earnings losses than the dichotomous variable of switching occupations. The F-test for the significance of both linear and quadratic forms of skills transferability also indicates that these two variables are highly jointly significant (F=10.34, $p<0.0001$), which implies that both forms of skills transferability add information to the model. In other words, compared with the result in column (3), adding the dichotomous variable (*$SAMEOCC_i$*) in column (4) does not add any information into the model (i.e., the adjusted R^2 does not change). This finding confirms the above hypothesis that skills transferability across occupations is a better measure of occupational human capital than the dichotomous variable of switching occupations. In other words, the effect of the dichotomous variable is captured by the skills transferability so that measuring the occupational human capital in terms of the degree of similarity between two occupations is more important than whether or not workers can find the same occupations as their previous jobs.

6.2 Robustness Tests

The results from the previous section present a strong relationship between earnings losses due to job displacement and occupational similarity as measured by skills transferability. However, as mentioned earlier, OLS estimates may be subject to selection bias because the process of reemployment is not random and wages are only observed for workers who are reemployed in the data. The relationship between skills transferability and earnings losses in a sample of displaced workers who are reemployed at the survey date might be quite different from the relationship observed in the labor force as a whole. For example, those who were not reemployed may have had different unobserved characteristics affecting their earnings from those of reemployed group. If this is the case, the OLS method could produce biased and inconsistent estimates.

One way to reduce the source of selection bias is to restrict the sample to workers who were displaced at least one year before the survey date because those workers displaced in the most recent years are less likely to be reemployed and hence report their weekly earnings (Neal, 1995). Table 17 presents the OLS results for this group of workers. Even though this restriction lowered the sample size by approximately 37 percent, the estimated transferability effect is very similar to those reported in Table 16. For example, column (2) shows that increasing the skills transferability by 10 percentage points, on average, lowers earnings losses by 3.8 percent, all else equal.

The more conventional correction for selection bias is to apply Heckman's (1979) two-step procedure. The process of this procedure applied to this context is as follows. First, I estimate the following probit regression of the probability of being reemployed at the survey date.

$$Empt^{*}_{i} = \beta' Z + \upsilon_i \qquad (3.5)$$

where $Empt^{*}_{i}$ is the latent variable for being reemployed at the survey date for worker *i*. We can observe workers *i* being reemployed if $Empt^{*}_{i} > 0$ and hence can observe all his/her post-displacement characteristics. Z is a vector of worker characteristics and work history. υ_i is the error term of unobserved worker characteristics with mean zero and constant variance, and it is assumed to be independent and identically distributed across individuals.

In general, *Z* should include all variables from the earnings losses regression and also contain at least one additional variable that is excluded from the earnings losses regression. If *Z* does not contain the excluded variable(s), then the identification of the model will rely completely on the functional form assumptions. Therefore, to satisfy this condition, at least one variable that affects the reemployment decision but does not directly affect earnings losses should be included in *Z*. The excluded variable proposed in this analysis is a dichotomous variable indicating whether the individual has a child under the age of two or five (*ch02, ch05*). I hypothesize that displaced workers who have children under two years old (*ch02*) or under five years old (*ch05*) might be less likely to seek reemployment conditioning on the other observed worker characteristics, but it should not directly influence their earnings reductions. Childcare responsibilities might increase the opportunity cost of getting a job and lower the probability of being employed (Podgursky and Swaim, 1987; Carrington, 1990).

The second step of this procedure is an OLS regression of log difference in real weekly earnings that includes the estimated coefficients from the probit regression (inverse of the Mills ratio). The results of Heckman's (1979) two-step procedure are reported in Table 18.

Column (1) presents Heckman's two-step estimates without the excluded variable, and column (2) presents the estimates with two additional excluded variables (*ch02* and *ch05*). Note that as the inverse of the Mills ratios are far from statistically significant, I can reject the hypothesis of sample selection implying that the corrections for selection bias contribute little to the results. The comparison of the corrected sample selection and OLS estimators shows that most of the coefficients, including skills transferability, are not greatly affected by correction for selection.[24] However, some other coefficients, such as the coefficient of industry switches are sensitive to the estimation method. This implies that the effect of skills transferability on the post-displacement earnings losses does not appear to be biased by selection into reemployment.[25] Thus, the results corrected for selection bias also support the hypothesis that displaced workers are compensated for occupation-specific skills, and workers who find occupations that are more similar to their pre-displacement jobs will suffer less earnings losses than those who find dissimilar occupations, thus confirming the importance of occupational human capital as a major determinant of earnings losses.

6.3 Comparison of the Effect of Shaw's and Ormiston's Skills Transferability

This subsection discusses the results comparing Shaw's and Ormiston's skills transferability at the 2-digit level. Similar to Table 16, column (1) of Table 19 shows the result of standard model of occupational human capital and earnings losses using a dichotomous variable of occupational switches at the 2-digit level. The coefficient of occupational switches is slightly higher than that at the 3-digit level (i.e., the coefficient estimate of staying at the same 3-digit occupation is 0.105 while the coefficient estimate of staying at the 2-digit occupation is 0.116). In particular, on average, staying at the same 2-digit occupation lowers earnings losses by 11.6 percent, all else equal. Next, column (2) and (3) present the effect of Ormiston's skills transferability on earnings losses at the 2-digit level. In general, the results look very similar to

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24 One of the reasons that the results do not change so much in this specification may be because of the weakness of the instrument or the excluded variation (*ch02, ch05*) in the identification of the participation bias term. Unfortunately, there does not appear to be another attractive alternative.

25 The other source of bias emanated from the omitted variables within reemployed displaced workers, such as luck, innate ability, and motivation, from the reduced form regression (Equation 3.1). If the worker who has more innate ability or motivation is the one to find a more similar post-displacement occupation and also has lower earnings loss, then the estimated coefficient will be biased and inconsistent.

those at the 3-digit level. For example, if the 2-digit skills transferability increases by 10 percentage points, on average, it reduces real weekly earnings losses by 3.3 percent, holding other factors fixed, and the estimated coefficient is statistically significant at the 1 percent level. Column (4) presents the regression results based on Shaw's skills transferability. It shows that if the Shaw's skills transferability increases by 10 percentage points, on average, it reduces real weekly earnings losses by 1.2 percent, holding other factors fixed. As we can see, compared to Ormiston's skills transferability, the magnitude of Shaw's skills transferability is approximately 3 times smaller than that of Ormiston's coefficient. This probably could be explained by the argument in Chapter 1 that the return to Shaw's skills transferability is contaminated by other social factors and by the market demand; therefore, the real return to Shaw's skills transferability would be lower. Column (5) shows the result of the non-linear relationship between earnings losses and Shaw's skills transferability. As we can see, the coefficients of both level and square terms are statistically insignificant. However, the F-test for the significance of both linear and quadratic forms of skills transferability indicates that these two variables are highly jointly significant ($F=6.85$, $p<0.001$).

To summarize, Table 19 shows that the rates of return to both approaches of skills transferability are statistically significant in the linear case although the magnitude of Shaw's skills transferability is lower than that of Ormiston's skills transferability. However, while Ormiston's skills transferability indicates evidence of non-linear relationship between earnings losses and skills transferability, Shaw's skills transferability does not.

7. Conclusions and Implications for Future Research

This chapter highlights the role of occupational human capital in determining the earnings losses after job displacement; in particular, the degree to which occupation-specific skills are transferable across occupations depends on the similarity between two given occupations. The key finding of this chapter is that occupational human capital, and more specifically, skills transferability between occupations, is an important determinant of changes in weekly earnings following displacement. In particular, the ordinary least square (OLS) estimates based on Ormiston's approach at the 3-digit level present that, on average, displaced workers whose new jobs measure 10 percentage points closer to their previous job on the occupational similarity measure experience approximately 3.6 percent less earnings losses *ceteris paribus*. This implies that the degree of similarity between pre- and post-displacement occupations has a strong effect on how displaced workers will suffer from earnings losses both in terms of significance and the magnitude of the effect. In addition, the relationship between occupational skills transferability and earnings losses are not linear: a higher degree of skills transferability lowers earnings losses, but the decline attenuates as skills transferability increases. Moreover, previous studies using a dichotomous variable indicating whether displaced workers find the same occupation imply convexity (in some sense, an infinite amount of convexity) in the relationship between earnings losses and occupational skills transferability. However, the results presented in this chapter suggest that previous results are wrong. Instead, the relationship between earnings losses and occupational skills transferability is concavity. In terms of the comparison of Shaw's and Ormiston's skill transferability at the 2-digit level, The findings show that the rates of return to both approaches of skills transferability are statistically significant in the linear case, although the magnitude of Shaw's skills transferability is lower than that of

Ormiston's skills transferability. In addition, both Ormiston's and Shaw's skills transferability indicate evidence of non-linear relationship between earnings losses and skills transferability.

This chapter's findings on earnings losses due to job displacement have important implications for researchers, policy makers, and the public. For future research, it sheds light on the role of occupational human capital in determining earnings losses after job displacement. In fact, the results show that displaced workers also receive compensation that is not completely general or specific to a particular firm, but rather specific to occupation. The findings from this chapter highlight the importance of occupational specific human capital in the employment relationship; losing these types of skills might result in substantial losses to the displaced workers' earnings. In addition, previous research on this topic has used a dichotomous variable indicating whether displaced workers remained in the same occupation as their pre-displacement job and ignored the fact that occupational skills could be (partially) transferable across occupations.

However, using the continuous variable of skills transferability, the results from this chapter indicate that if displaced workers could find occupations that are very similar, if not exactly the same as their old jobs, they can transfer most of their previous occupational skills to the new job and their earnings losses would be reduced. Moreover, the findings indicate that the measure of skills transferability is a better measure of occupational human capital than the dichotomous variable of switching occupations. Thus, those performing future research regarding occupational human capital should consider applying this measure to other outcome variables as well. For example, this chapter only examines the effect of occupational skill transferability on the loss of earnings between pre- and post-displacement occupations and does not consider the effect on other types of benefits. Thus, it might be interesting for future research to investigate the effect of occupational human capital, especially skills transferability, on total compensation, which also includes other benefits such as health insurance and pensions (Podgursky and Swaim, 1987).

From a policy perspective, these findings provide valuable guidance for the development of government programs to help displaced workers. The government has spent an enormous amount on helping this group of workers. For example, the 1988 Economic Dislocation and Worker Adjustment Assistance Act provides one billion dollars annually for retraining displaced workers (Carrington and Zaman, 1994). In addition, the amount of money the unemployment insurance benefit (UI) allocates to displaced workers each year is tremendously high, around $76 billion in 2009 and $58 billion in 2010. The government has also promoted various new and expensive programs including job-search assistance and job counseling programs to help eligible displaced workers find new jobs. Specifically, the objective of this job-search assistance is to help displaced workers return to work as soon as possible in order to increase their short-run earnings. The results of this chapter point toward a program to retrain displaced workers while maintaining their occupation-specific skills; in particular, the program would assist those who work in occupations that do not have many similar counterparts. To assist those workers who have a hard time finding a new occupation with high skills transferability, the training program might also build new occupational skills so that workers could have occupations to choose from by increasing skills transferability. In addition, these results suggest that a displaced worker assistance program would focus on matching displaced workers with jobs that are similar, if not exactly the same, as their pre-displacement occupations to help reduce the short-run earnings losses of displaced workers. Moreover, it also suggests that earnings losses are likely to be greatest for those in occupations where there is a low chance of re-employment in a similar occupation. Therefore, it lays out a basis for differential aid by occupation.

Table 15. Percentage of Reemployed Workers Who Change Occupations

Full Sample	1994	1996	1998	2000	2002	2004	2006	2008	2010
Different Occupation (percent)	69.74	71.12	71.26	67.43	69.35	65.52	63.88	65.60	61.72

Figure 2. The Fractions of Displaced Workers by Level of Skills Transferability

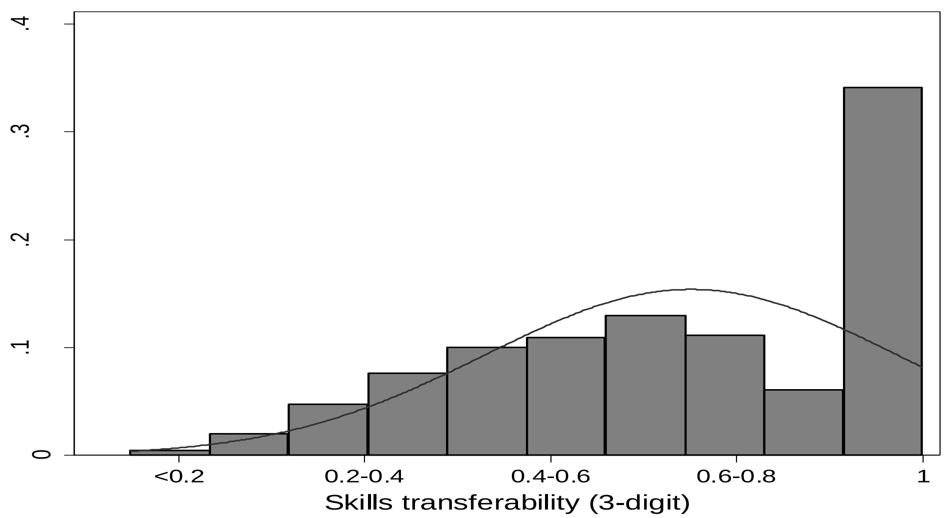

Figure 3. The Average Change in ln (real weekly earnings) by Level of Occupational Skills Transferability between Pre- and Post-Displacement Occupations

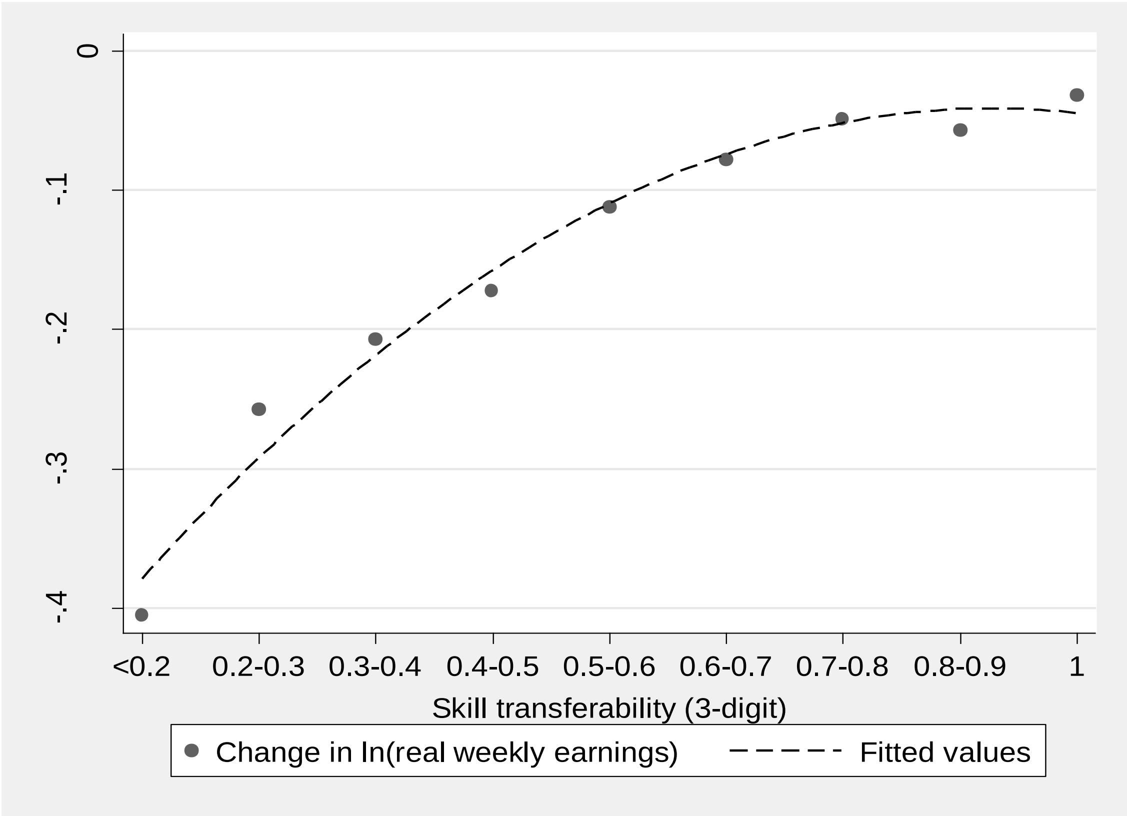

Table 16. The Earnings Losses Regression

	Dependent Variable: Difference in log of real weekly earnings ($2010; OLS)			
Independent Variable	(1)	(2)	(3)	(4)
Same Occupation (0/1)	0.105			-0.004
	(6.28)			(-0.09)
Same Industry (0/1)	0.083	0.064	0.072	0.072
	(4.73)	(3.62)	(4.03)	(4.06)
Transferability*100		0.0036	0.0093	0.0091
		(9.37)	(3.12)	(2.21)
Transferability^2			-0.00004	-0.00004
			(-1.99)	(-1.19)
Firm Tenure (at the lost job)	-0.008	-0.008	-0.008	-0.008
	(-5.08)	(-4.91)	(-4.91)	(-4.91)
Union Status (at the lost job, 0/1)	-0.121	-0.122	-0.123	-0.123
	(-3.64)	(-3.69)	(-3.70)	(-3.70)
Advanced Notice (0/1)	0.014	0.011	0.010	0.010
	(0.84)	(0.62)	(0.60)	(0.60)
Health Insurance (at the lost job, 0/1)	-0.001	-0.004	-0.003	-0.003
	(-0.07)	(-0.20)	(-0.15)	(-0.15)
UI Benefit (0/1)	-0.043	-0.045	-0.045	-0.045
	(-2.43)	(-2.51)	(-2.53)	(-2.53)
UI Ended (0/1)	-0.194	-0.186	-0.185	-0.185
	(-6.64)	(-6.38)	(-6.36)	(-6.36)
Full-time Job (at the lost job, 0/1)	-0.313	-0.314	-0.315	-0.315
	(-9.08)	(-9.10)	(-9.12)	(-9.12)
Age	0.015	0.014	0.015	0.015
	(2.54)	(2.47)	(2.49)	(2.49)
Age^2	-0.0002	-0.0002	-0.0002	-0.0002
	(-3.02)	(-2.97)	(-2.98)	(-2.98)
Female	-0.089	-0.092	-0.094	-0.094
	(-4.35)	(-4.51)	(-4.58)	(-4.58)
N	6,827	6,827	6,827	6,827
Adj. R^2	0.0778	0.0845	0.0850	0.0849

Note: t-statistics are in the parentheses. Not included as independent variables are 10 major occupation dummies, 10 major industry dummies, marital status, US citizen dummy, race dummies (i.e., black, white, Hispanic), dummy of geographic moves, unemployment rate at year of survey across state, year of displacement, and 4 education levels.

Table 17. The Earnings Losses Regression Excluding Workers Who Were Displaced at Least One Year before the Survey Date

	Dependent Variable: Difference in log of real weekly earnings ($2010; OLS)			
Independent Variable	(1)	(2)	(3)	(4)
Same Occupation (0/1)	0.108			-0.015
	(4.75)			(-0.28)
Same Industry (0/1)	0.099	0.079	0.087	0.088
	(3.99)	(3.25)	(3.54)	(3.55)
Transferability*100		0.0038	0.0105	0.0096
		(7.99)	(3.27)	(2.12)
Transferability^2			-0.00005	-0.00004
			(-2.09)	(-1.07)
Firm Tenure (at the lost job)	-0.010	-0.010	-0.010	-0.010
	(-5.87)	(-5.74)	(-5.73)	(-5.72)
Union Status (at the lost job, 0/1)	-0.136	-0.138	-0.138	-0.139
	(-3.61)	(-3.69)	(-3.70)	(-3.70)
Advanced Notice (0/1)	-0.003	-0.007	-0.007	-0.007
	(-0.17)	(-0.34)	(-0.35)	(-0.36)
Health Insurance (at the lost job, 0/1)	-0.006	-0.009	-0.008	-0.008
	(-0.27)	(-0.38)	(-0.35)	(-0.35)
UI Benefit (0/1)	0.007	0.007	0.007	0.007
	(0.28)	(0.28)	(0.29)	(0.29)
UI Ended (0/1)	-0.206	-0.196	-0.194	-0.194
	(-7.03)	(-6.71)	(-6.66)	(-6.66)
Full-time Job (at the lost job, 0/1)	-0.295	-0.297	-0.299	-0.299
	(-7.93)	(-8.02)	(-8.06)	(-8.06)
Age	0.013	0.011	0.012	0.012
	(1.83)	(1.68)	(1.69)	(1.69)
Age^2	-0.0002	-0.0002	-0.0002	-0.0002
	(-2.45)	(-2.31)	(-2.31)	(-2.31)
Female	-0.093	-0.094	-0.096	-0.096
	(-4.10)	(-4.17)	(-4.26)	(-4.25)
N	4,308	4,308	4,308	4,308
Adj. R^2	0.0882	0.0969	0.0976	0.0974

Note: t-statistics are in the parentheses. Not included as independent variables are 10 major occupation dummies, 10 major industry dummies, marital status, US citizen dummy, race dummies (i.e., black, white, Hispanic), dummy of geographic moves, unemployment rate at year of survey across state, year of displacement, and 4 education levels.

Table 18. Heckman's Two-Step Estimation of the Earnings Losses

	Dependent Variable: Difference in log of real weekly earnings ($2010)		
	No Excluded variable	Excluded variable: *ch02, ch05*	OLS
Independent Variable	(1)	(2)	(3)
Same Industry (0/1)	0.129	0.089	0.064
	(1.77)	(0.85)	(3.62)
Transferability*100	0.0038	0.0038	0.0036
	(6.08)	(4.99)	(9.37)
Firm Tenure (at the lost job)	-0.007	-0.007	-0.008
	(-3.53)	(-3.14)	(-4.91)
Union Status (at the lost job, 0/1)	-0.074	-0.065	-0.122
	(-1.83)	(-1.41)	(-3.69)
Advanced Notice (0/1)	0.034	0.048	0.011
	(1.48)	(1.80)	(0.62)
Health Insurance (at the lost job, 0/1)	-0.039	-0.022	-0.004
	(-1.15)	(-0.51)	(-0.20)
UI Benefit (0/1)	-0.046	-0.094	-0.045
	(-0.99)	(-1.37)	(-2.51)
UI Ended (0/1)	-0.228	-0.237	-0.186
	(-6.18)	(-5.49)	(-6.38)
Full-time Job (at the lost job, 0/1)	-0.442	-0.465	-0.314
	(-11.68)	(-10.23)	(-9.10)
Age	0.015	0.017	0.014
	(2.28)	(2.05)	(2.47)
Age^2	-0.0002	-0.0003	-0.0002
	(-2.86)	(-2.65)	(-2.97)
Female	-0.087	-0.087	-0.092
	(-3.19)	(-2.81)	(-4.51)
Inverse Mill Ratio	-0.159	0.026	
	(-0.69)	(0.08)	
N	12,984	10,239	6,827

Note: t-statistics are in the parentheses. Not included as independent variables are 10 major occupation dummies, 10 major industry dummies, marital status, US citizen dummy, race dummies (i.e., black, white, Hispanic), dummy of geographic moves, unemployment rate at year of survey across state, year of displacement, and 4 education levels.

Table 19. Comparison of the Return to Shaw's and Ormiston's Skills Transferability

	Dependent Variable: Difference in log of real weekly earnings ($2010; OLS)				
Independent Variable	(1)	(2)	(3)	(4)	(5)
Same Occupation (0/1)	0.116				
	(7.27)				
Ormiston transfer*100		0.0033	0.0141		
		(9.24)	(3.32)		
Ormiston transfer^2*100			-0.0001		
			(-2.55)		
Shaw transfer*100				0.0012	0.0125
				(7.29)	(1.26)
Shaw transfer^2*100					-0.0001
					(-1.14)
Same Industry (0/1)	0.087	0.077	0.082	0.087	0.089
	(5.31)	(4.75)	(4.99)	(5.31)	(5.38)
Firm Tenure (at the lost job)	-0.009	-0.008	-0.008	-0.009	-0.009
	(-5.26)	(-5.17)	(-5.14)	(-5.25)	(-5.24)
Union Status (at the lost job, 0/1)	-0.101	-0.101	-0.101	-0.102	-0.102
	(-3.18)	(-3.19)	(-3.19)	(-3.18)	(-3.21)
Advanced Notice (0/1)	0.012	0.011	0.010	0.012	0.012
	(0.73)	(0.65)	(0.58)	(0.73)	(0.73)
Health Insurance (at the lost job, 0/1)	-0.014	-0.016	-0.015	-0.014	-0.013
	(-0.78)	(-0.92)	(-0.86)	(-0.78)	(-0.77)
UI Benefit (0/1)	-0.040	-0.040	-0.040	-0.040	-0.040
	(-2.38)	(-2.38)	(-2.39)	(-2.38)	(-2.37)
UI Ended (0/1)	-0.198	-0.194	-0.193	-0.198	-0.198
	(-7.02)	(-6.91)	(-6.89)	(-7.02)	(-7.01)
Full-time Job (at the lost job, 0/1)	-0.312	-0.314	-0.313	-0.312	-0.312
	(-9.41)	(-9.44)	(-9.43)	(-9.41)	(-9.39)
Age	0.014	0.013	0.013	0.014	0.014
	(2.53)	(2.41)	(2.39)	(2.54)	(2.57)
Age^2	-0.0002	-0.0002	-0.0002	-0.0002	-0.0002
	(-3.09)	(-2.98)	(-2.95)	(-3.09)	(-3.12)
Female	-0.0805	-0.0817	-0.0844	-0.0806	-0.0817
	(-4.19)	(-4.26)	(-4.37)	(-4.19)	(-4.25)
N	7,469	7,469	7,469	7,469	7,469
Adj. R^2	0.0793	0.0829	0.0837	0.0794	0.0795

Note: t-statistics are in the parentheses. Not included as independent variables are 10 major occupation dummies, 10 major industry dummies, marital status, US citizen dummy, race dummies (i.e., black, white, Hispanic), dummy of geographic moves, unemployment rate at year of survey across state, year of displacement, and 4 education levels.

Appendices

APPENDIX A

Appendix Table A1. Knowledge, Skill, and Ability Categories across Occupations as Defined by O*NET

Knowledge	Skill	Ability
Administration and Management	Active Learning	Arm-hand Steadiness
Biology	Active listening	Auditory Attention
Building and Construction	Complex Problem Solving	Category Flexibility
Chemistry	Coordination	Control Precision
Clerical	Critical Thinking	Deductive Reasoning
Communications and Media	Equipment Maintenance	Depth Perception
Computers and Electronics	Equipment Selection	Dynamic Flexibility
Customer and Personal Service	Installation	Dynamic Strength
Design	Instructing	Explosive Strength
Economics and Accounting	Judgment and Decision Making	Extent Flexibility
Education and Training	Learning Strategies	Far Vision
Engineering and Technology	Management of Financial Resources	Finger Dexterity
English Language	Management of Material Resources	Flexibility of Closure
Fine Arts	Management of Personnel Resources	Fluency of Ideas
Food Production	Mathematics	Glare Sensitivity
Foreign Language	Monitoring	Gross Body Coordination
Geography	Negotiation	Gross Body Equilibrium
History and Archeology	Operation and Control	Hearing Sensitivity
Law and Government	Operation Monitoring	Inductive Reasoning
Mathematics	Operation Analysis	Information Ordering
Mechanical	Persuasion	Manual Dexterity
Medicine and Dentistry	Programming	Mathematical Reasoning
Personnel and Human Resources	Quality Control Analysis	Memorization
Philosophy and Theology	Reading Comprehension	Multilimb Coordination
Physics	Repairing	Near Vision
Production and Processing	Science	Night Vision
Psychology	Service Orientation	Number Facility
Public Safety and Security	Social Perceptiveness	Oral Comprehension
Sales and Marketing	Speaking	Oral Expression
Sociology and Anthropology	System Analysis	Originality
Telecommunications	System Evaluation	Perceptual Speed
Therapy and Counseling	Technology Design	Peripheral Vision
Transportation	Time Management	Problem Sensitivity

Appendix Table A1. Knowledge, Skill, and Ability Categories across Occupations as Defined by O*NET (Cont’d)

Knowledge	Skill	Ability
	Troubleshooting	Rate Control
	Writing	Reaction Time
		Response Orientation
		Selective Attention
		Sound Localization
		Spatial Orientation
		Speech Clarity
		Speech Recognition
		Speed of Closure
		Speed of Limb Movement
		Stamina
		Static Strength
		Time Sharing
		Trunk Strength
		Visual Color Discrimination
		Visualization
		Wrist-finger Speed
		Written Comprehension
		Written expression

APPENDIX B

Description of the Main Variables in the NLSY Dataset

In Chapter 2, the analysis focuses on the so-called “CPS” job (firm), which is defined as the current or most recent employer at the date of interview. In each survey year, an individual can have up to five different jobs (employers), and the one that is the current or most recent would be assigned as a CPS job. The detailed job information for each CPS job, regardless of whether it is a full- or part-time job, has been used to construct the key variables of this analysis.

The following explains in more detail the key variables used in this analysis.

1. Firm Tenure: Firm tenure is measured based on the actual start date to stop date at each interview and added together between survey periods. For example, one individual starts working for Firm A on June 1, 1980 and is interviewed on June 31, 1980. He is still working for that firm on August 2, 1981, when he is interviewed again. He continues to work for the same firm until April 5, 1982, when he changes jobs. He is interviewed again on August 10, 1982. A cumulative firm tenure at Firm A in number of weeks could be constructed as follows:

Tenure 1= [Tenure from June 1, 1980 to June 31, 1980 at the 1980 interview]

Tenure 2 = Tenure 1 + [Tenure from July 1, 1980 to August 2, 1981 at the 1981 interview]

Tenure 3 = Tenure 1 + Tenure 2 + [Tenure from August 3, 1981 to April 5, 1982, the date that he left this firm at the 1982]

where Tenure1 is the current firm tenure in the year 1980, Tenure 2 is the firm tenure in the year 1981, and Tenure 3 is the firm tenure in the year 1982.

Note that there is a possibility of double-counting employers. Up until 1998, the employers were only tracked between two contiguous interview years; therefore, an individual who works for a particular firm during the first year, leaves that firm next year, and then returns to work at the same firm later after a year or more would be determined to work for a new firm during the second tenure since the previous tenure would have been out of the tracking scopes. As a result of double-counting employers, there is a possibility of firm tenure with a single firm being calculated as tenure with two separate employers, and unfortunately there is no systematic way to measure how often this event might occur. After 1998, however, the computer-based interview system began to keep track of all employers so that it recognized when an individual returned to the same employer that he/she left a number of years earlier. In addition, there is also a gap within the reported start to stop date (a "between-job" gap) for a specific firm in which an individual is not actively working for that employer, but does not consider himself completely disassociated from that firm during these periods. Thus, the total tenure with that firm will not account for these gaps because they occur before the individual has reported an actual stop date for association with that firm, so these weeks of gaps would be considered as part of his tenure for that firm.

2. Actual Labor Market Experience: This measures the total years of work experience in a labor market accumulated as a full-time or part-time employee since the first interview up to the time of the NLSY interview. One advantage of the NLSY is that it is a longitudinal data that reports the number of weeks worked for each year in the sample and obtains this information retrospectively for the years preceding the sample. This allows us to construct the measure of actual labor market experience, which is the key variable in this analysis. Specifically, I used the question that asks for the "number of weeks worked since the last interview" of each individual. Then, I added them together and divided this number by 52 to obtain the yearly actual labor market experience for each individual.

3. Occupation and Industry Tenure: For the 3-digit level of occupation and industry tenure measures, I used the CPS occupation/industry of individual, which is defined as "the current or most recent occupation/industry that the individual has during the survey week." Given the CPS occupation/industry for each individual across year, I can construct both occupation and industry tenures directly by comparing each individual's occupation and industry year by year. If the occupation/industry between two consecutive years were reported as being the same, then I would assume that individual worked for that occupation/industry for the whole year. In that case, I can add the number of weeks worked since the last interview (divided by 52) into the occupation/industry tenure. Note that it is possible that an individual holds more than one occupation/industry within the same firm during the time of the interviews, but only the occupation/industry reported at the interview would be the current/most recent occupation/industry. In addition, in some cases, the occupation and industry codes are missing because individuals declined to give information about the type of work they performed. In other cases, the codes are missing because errors were made during processing the descriptions of the individuals' jobs. These errors would create "invalid skips" in the occupation and industry data. In addition, in many cases, the codes are missing because the individuals have never been asked about certain characteristics of a particular job. This happened in some, but not all, cases where jobs either involved less than 10 hours of work per week or less than 9 weeks of actual work. These missing codes would create "valid skips" in the data (Neal, 1999).

4. Hourly Wage: Hourly wage is calculated if the individual indicates that he is paid on an hourly basis. For those individuals who are not paid hourly, the coder calculates the hourly wage based on the respondent's time unit of pay and the usual hours worked per day or week.

5. Married: For simplicity, this dummy variable takes the value of "1" if an individual is married and "0" otherwise (i.e., single, divorced, separated, widowed).

6. Regional dummies: these dummies include the North East, North Central, West, and South.

7. SMSA: This dummy variable takes the value of "1" if an individual is living in a SMSA and "0" otherwise.

8. Major Occupation Dummies: Thirteen dummy variables represent the 1-digit 1980 census occupations as follows:

-Executive, administrative, and managerial

-Professional specialty

-Technicians and related support

- Sales

-Administrative support, including clerical

-Private household services

-Protective services

-Services, except protective and household

-Farming, forestry, and fishing

-Precision production, craft, and repair

-Machine operators, assemblers, and inspectors

-Transportation and material moving equipment

-Handlers, equipment cleaners, helpers, and laborers

9. Major industry dummies: These 13 dummy variables represent the 1-digit 1980 census industry as follows:

-Agriculture, forestry, and fisheries

-Mining

-Construction

-Manufacturing durable goods

-Transportation and communications

-Wholesale trade

-Retail trade

-Finance, insurance, and real estate

-Business and repair services

-Personal services

-Entertainment and recreation services

-Professional and related services

10. Dummy variable of old firm: A dummy variable equals “1” if the firm tenure is greater than 1 and “0” otherwise. The reason for including this variable is that the first year of work with an employer typically requires more investment in job-related skills (Parent, 2000).

Appendix Table B1. Sample Construction

NLSY total sample	12,686	
Deletions		Remaining sample
Military sample	1,280	11,406
Female	5,827	5,579
Non-white	1,795	3,784
School returners	966	2,818
Leaving the survey forever after the first interview	35	2,783
Missing occupation more than 13 years	228	2,555
Being in the military at any time	197	2,358
Firm tenure at 1979 > 2 years	49	2,309

Appendix Table B2. Descriptive statistics of all variables from 1979-2000

Variable	Mean	Std. Dev.
Real hourly wage ($1979)	5.70	3.61
Age	27.43	5.82
Education	12.22	2.31
Percent married	0.48	0.50
Hours worked per week	42.29	11.48
Occupation tenure (3-digit)	2.45	2.46
Occupation tenure (2-digit)	3.19	3.11
Occupational investment (3-digit)	3.29	2.80
Occupational investment (2-digit, Shaw's approach)	3.30	3.12
Occupational investment (2-digit, Ormiston's approach)	4.27	3.42
Industry tenure (3-digit)	3.40	3.49
Industry tenure (2-digit)	3.96	3.85
Firm tenure	3.41	3.91
Firm tenure >1 (0/1)	0.66	0.47
Number of firms changed	3.71	2.57
Labor market experience	8.12	5.33
SVP (0/1)	5.14	1.71
TQ (0/1)	1.53	1.10
Job zone (0/1)	2.57	0.97
Married (0/1)	0.48	0.50
Live in North East (0/1)	0.18	0.39
Live in North Central (0/1)	0.28	0.45
Live in South (0/1)	0.32	0.47
Live in SMSA (0/1)	0.75	0.43
Major Occupation		
Executive and Managerial (0/1)	0.09	0.28
Professional (0/1)	0.06	0.23
Technicians (0/1)	0.03	0.17
Sales (0/1)	0.08	0.28
Administrative support (0/1)	0.07	0.25
Private household service (0/1)	0.00	0.02
Protective service (0/1)	0.01	0.10
Service, except protective (0/1)	0.09	0.29

Appendix Table B2. Descriptive statistics of all variables from 1979-2000 (Cont'd)

Variable	Mean	Std. Dev.
Farming, forestry, and fishing (0/1)	0.05	0.21
Craft, precision production (0/1)	0.24	0.43
Machine operators (0/1)	0.11	0.31
Transportation (0/1)	0.08	0.28
Handlers (0/1)	0.10	0.30
Major industry		
Agriculture, forestry, and fisheries (0/1)	0.05	0.21
Mining (0/1)	0.02	0.13
Construction (0/1)	0.14	0.35
Manufacturing Durable goods (0/1)	0.16	0.37
Manufacturing Nondurable goods (0/1)	0.09	0.28
Transportation, communications (0/1)	0.08	0.27
Wholesale trade (0/1)	0.05	0.21
Retail trade (0/1)	0.18	0.39
Finance, insurance, and real estate (0/1)	0.03	0.18
Business and repair services (0/1)	0.09	0.28
Personal services (0/1)	0.02	0.15
Entertainment and recreation services (0/1)	0.02	0.13
Professional and related services (0/1)	0.07	0.26
Number of Observations	26,818	
Number of Individuals	2,309	

APPENDIX C

The Estimations of Occupational Skills Intensity

Besides occupational skills transferability, the skills intensity—the level of skills acquisition of occupational human capital—is also another aspect of occupational human capital neglected in the past literature. Most studies on the wage determination process assume there is the same rate of acquisition of occupational tenure across various occupations although the level of skills acquisition of occupational human capital is largely determined by the type of occupation held. Some occupations provide relatively limited prospects for capital acquisition, while some occupations provide extensive human capital acquisition opportunities. Thus, in Chapter 2, I also control for the skills intensity at the current occupation in the wage equation. In order to estimate this occupational skills intensity measure, I use the following variables.

The first variable is called the Standard Vocational Preparation (*SVP*) from the O*NET dataset. The *SVP* provides information regarding the required level of knowledge and skills for a particular occupation, rated on a nine-point scale.[26] Specifically, the definition of *SVP* is "the amount of time required by a typical worker to learn the techniques, acquire the information, and develop the facility needed for average performance in a specific job-worker situation" (Oswald et al., 1999, pg. 4). It includes training acquired in a school, work, military, institutional, or vocational environment, but excludes schooling without specific vocational content. Appendix Table C1 represents the rating scale that is used to specify the value of *SVP*.

The average score of *SVP* over 467 (3-digit) occupations shown in Appendix Table C2 is approximately 5.74. The average *SVP* of financial manager is around 7.66 (i.e., on average, a

[26] The *SVP* is originally estimated based on the Standard Occupational Classification (SOC) code, and then it is matched to the U.S. Census code for this analysis.

financial manager requires two to over four years to develop the skills in this occupation) while the *SVP* of the construction laborer is 3.26 (i.e., on average, a construction laborer requires one to three months to develop the skills in this occupation). This implies that the skills intensity of financial manager is much higher than that of construction laborer.

The primary advantage of this measure is that the level of the *SVP* requirement for an occupation can be directly linked to the level of specific occupational education and training achieved by an individual. In addition, it allows individuals to prepare to be able to perform effectively in an occupation (Oswald et al., 1999). On the other hand, its main disadvantage is that it is highly correlated with education (i.e., more educated individuals might take a shorter time period to acquire needed skills), and also it is, to some extent, an arbitrary measure based on estimates made by researchers of the Bureau of Employment Security for the 4000 jobs of the Dictionary of Occupational Titles (DOT) (Shaw, 1981).

The second variable of occupational skills intensity is from the direct measure of on-the-job training, labeled as "*TQ*," available in the 1985 and 1993 PSID. It is calculated in fractions of year based on the mean response of a representative national sample between the ages of 18 to 64. In particular, individuals, including both household heads and wives, respond to the question: "On a job like yours, how long would it take the average new person to become fully trained and qualified?" (Duncan and Hoffman, 1979, pg. 596) This question is designed to measure the volume of training attached to the current job and acquired on the job.[27] The main advantage of this variable is that it is formed by those individuals who actually work in the occupation, and it appears less correlated with education (Shaw, 1981). However, the *TQ* could be an imprecise

[27] The question uses the term "the average new person" rather than "you" in order to minimize the responded training differences due to skills or experience unique to that individual (Duncan and Hoffman, 1979).

proxy of skills intensity because even the training in two jobs with equal training time periods could have different degrees of intensity (Duncan and Hoffman, 1979). Appendix Table C2 demonstrates the distribution of the average *TQ* scores of 14 selected occupations. On average, it takes 1.92 years for individuals to be fully trained and qualified in their current occupations. Financial managers require approximate 3.64 years, while bakers require only 0.93 years to become fully trained, and the automobile mechanics need around 1.33 years.

The third variable is called a *JobZone*, also from the O*NET dataset. It is a five-level scale based on data from job incumbents and occupational experts (OEs) regarding the levels of education, experience, and training needed for work in their occupations as displayed in Appendix Table C3. Each occupation is assigned to one of five *JobZones*—groups of occupations that require similar amounts of vocational preparation. Occupations in *JobZone 1* require the least vocational preparation (i.e., the least skills intensity); occupations in *JobZone 5* require the most vocational preparation (i.e., the highest skills intensity).

Appendix Table C2 demonstrates that the average *JobZone* score of financial managers is 4.50, which implies the considerable to extensive preparation needed for work in this occupation. On the other hand, bank tellers are in *JobZone 2*, implying some preparation needed for work in this occupation.

In some cases, the estimates of *SVP*, *TQ*, and *JobZone* are difficult to interpret. For example, one might feel suspicious that the *TQ* measure for workers at amusement and recreation facilities is higher than that of economists. Also, cashiers require 0.17 years while barbers require about 1.50 years. Another concern is whether the training time required to estimate these measures to become an average; for example, a locomotive engineer could begin his career when he moves up from fireman, when he takes his initial job with the railroad, or at some other time (Scoville, 1966). Therefore, these estimates require some careful interpretation.

Comparing the *SVP*, *TQ*, and *JobZone*, Appendix Table C4 provides the correlations among these three variables. In general, the correlation among *SVP*, *TQ*, and *JobZone* are fairly high and positive. For example, the correlation between *SVP* and *TQ* is 0.67, while the correlation between *TQ* and *JobZone* is around 0.50. Thus, they are hypothesized to be a proxy of the occupational skills intensity.

Appendix Table C1. The *SVP* Levels and Definition

SVP level	Approximate required training time in years
1	0.00
2	0.04
3	0.17
4	0.38
5	0.75
6	1.50
7	3.00
8	7.00
9	12.00

Appendix Table C2. The Average *SVP*, *TQ*, and *JobZone* Scores for 14 Selected Occupations

Occupation (1980 Census code)	*SVP*	*TQ*	*JobZone*
All occupations (Mean)	5.74	1.92	2.87
Financial manager (7)	7.66	3.64	4.50
manager and administrator (19)	7.02	1.90	3.80
Architects (43)	7.92	5.96	4.50
Librarian (164)	6.40	2.12	5.00
Economists(166)	6.92	4.34	4.50
cashier (276)	2.97	0.18	1.50
Bank teller (383)	5.04	0.82	2.00
Barbers (457)	6.02	0.74	3.00
Automobile mechanics (505)	6.38	1.33	3.00
Baker (687)	6.37	0.93	2.00
Rolling machine operators (707)	3.72	0.08	3.00
Construction laborers(869)	3.26	1.17	1.50
Truck drivers (804, 805)	3.54	0.65	-
Attendants, amusement and recreation facilities (459)	3.58	4.57	1.78

Appendix Table C3. The *JobZone* Levels and Definition

JobZone	Preparation Level
1	Little or No preparation needed
2	Some preparation needed
3	Medium preparation needed
4	Considerable preparation needed
5	Extensive preparation needed

Appendix Table C4. Correlations among Three Skills Intensity Measures

Skills intensity measure	*SVP*	*TQ*	*JobZone*
SVP	1.00		
TQ	0.67	1.00	
JobZone	0.69	0.50	1.00

Appendix D

Appendix Table D1. Descriptive Statistics of Displaced Workers (2004–2010)

Variable	Mean	Std. Dev.
Difference in the natural logarithm of real weekly earnings (in $2010)	-0.21	0.68
Difference in the real weekly earnings (in $2010)	-121.15	454.86
Weekly earning at the lost job	773.68	625.93
Weekly earning at the current job	685.01	575.42
Occupational skills transferability	75.44	21.95
Same Occupation (0/1)	0.33	0.47
Same Industry (0/1)	0.29	0.45
Female (0/1)	0.44	0.50
Age	39.43	11.25
Less than high school (0/1)	0.07	0.26
High school (0/1)	0.33	0.47
Some college degree (0/1)	0.34	0.47
College degree (0/1)	0.20	0.40
Advanced degree (0/1)	0.07	0.25
Years of firm tenure at the lost job	4.81	6.23
Union status at the lost job (0/1)	0.09	0.28
Married (0/1)	0.56	0.50
Advanced notice (0/1)	0.36	0.48
Health insurance at the lost job (0/1)	0.58	0.49
UI benefit (0/1)	0.43	0.50
UI ended (0/1)	0.14	0.35
US citizen (0/1)	0.93	0.26
Moved geographically (0/1)	0.15	0.35
Full-time at the lost job (0/1)	0.90	0.31
White (0/1)	0.75	0.44
Black (0/1)	0.09	0.28
Hispanic (0/1)	0.12	0.32

Appendix Table D1. Descriptive Statistics of Displaced Workers (2004–2010) (Cont'd)

Variable	Mean	Std. Dev.
Year of displacement =2009 (0/1)	0.11	0.32
Year of displacement =2008 (0/1)	0.10	0.30
Year of displacement =2007 (0/1)	0.14	0.35
Year of displacement =2006 (0/1)	0.07	0.25
Year of displacement =2005 (0/1)	0.13	0.34
Year of displacement =2004 (0/1)	0.07	0.26
Year of displacement =2003 (0/1)	0.18	0.38
Year of displacement =2002 (0/1)	0.10	0.30
Year of displacement =2001(0/1)	0.10	0.30
State unemployment rate	6.23	2.31
Major Occupation		
Management (0/1)	0.14	0.35
Professional (0/1)	0.17	0.37
Service (0/1)	0.11	0.32
Sales (0/1)	0.10	0.30
Clerical (0/1)	0.15	0.36
Farming, fishing, and forestry (0/1)	0.01	0.07
Construction (0/1)	0.10	0.30
Installation, maintenance, and repair (0/1)	0.05	0.22
Production (0/1)	0.11	0.31
Transportation (0/1)	0.07	0.25
Major industry		
Agriculture (0/1)	0.01	0.08
Mining (0/1)	0.01	0.09
Manufacturing (0/1)	0.20	0.40
Wholesale and retail trade (0/1)	0.15	0.35
Information (0/1)	0.04	0.19
Financial (0/1)	0.08	0.27
Professional and business services (0/1)	0.13	0.34
Educational and health services (0/1)	0.11	0.31
Leisure and hospitality (0/1)	0.08	0.27
Other services (0/1)	0.03	0.18

Appendix Table D2. Descriptive Statistics for CPS and DWS (2004–2010)

	CPS		DWS	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Female (0/1)	0.51	0.50	0.44	0.50
Weekly pay at the current job ($)	789.89	628.23	685.01	575.42
Age	40.21	11.92	39.43	11.25
Less than high school (0/1)	0.080	0.27	0.07	0.26
High school (0/1)	0.30	0.46	0.33	0.47
Some college (0/1)	0.29	0.46	0.34	0.47
College (0/1)	0.22	0.41	0.20	0.40
Advanced college (0/1)	0.11	0.31	0.07	0.25
Married (0/1)	0.59	0.49	0.56	0.50
White (0/1)	0.74	0.44	0.75	0.44
Black (0/1)	0.09	0.29	0.09	0.28
Number of workers	47,480		6,827	

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