Career Trajectories of Displaced Workers: A Task-Specific Human Capital Approach

Mallika Pung[1] and Curtis J. Simon [2]

[1]New Mexico Department of Transportation
[2]Department of Economics, Clemson University

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Abstract

Research shows that the earnings of displaced workers decline more for those who switch occupations, more so when the skills employed on the new job differ more from those used in the lost job, and when the new job requires "fewer skills" than the lost job. We explain these regularities, and make new predictions using a heuristic, task-specific human capital model in which career trajectories are described by two components (1) skill composition and (2) hierarchical rank. The model that shows that larger changes in skill composition translate into larger reductions in rank, and hence earnings. The model also shows that changes in skill composition interact negatively with lost job rank. We test the implications of the model using data on full-time workers from the 1994-2018 Displaced Workers Surveys. We measure hierarchical rank as an occupation's place in the wage distribution, and changes in task composition as angular separation between skill vectors based on data from the Dictionary of Occupational Titles. We identify causal effects of changes in skill composition by instrumenting for displaced workers' angular separation with occupation-specific means for *non-displaced* workers, and vice versa. The estimated causal effects are surprisingly similar for displaced and non-displaced workers, suggesting that similar economic forces are at work.

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1 Introduction

Researchers have long interpreted the earnings losses of displaced workers as evidence of some form of "lost" specific human capital. That those losses are higher for those displaced from longer tenure jobs is consistent with the loss of human capital specific to the firm. However, other research suggests that human capital is at least partly transferable between firms. For example, earnings losses are smaller for those who find new jobs in their old occupation. Also, earnings losses among those who do switch occupations are smaller when the skills used in the new occupation are similar to those used in the old occupation (Poletaev and Robinson, 2008; Robinson, 2018). Moreover, Robinson (2018) finds that the negative effects of changes in job skill portfolio on earnings are limited to displaced workers who moved to less-skilled jobs. The partial transferability of human capital indicates that human capital is better thought of as task-specific rather than firm- or occupation-specific (Gathmann and Schönberg, 2010; Gibbons and Waldman, 2004; Lazear, 2009; Sullivan, 2010).

We explain these regularities, and make new predictions using a heuristic, task-specific human capital model in which career trajectories are described by two components (1) the composition of skills and (2) hierarchical rank. The model shows that changes in skill composition and changes in hierarchical rank are intimately linked. The maximum rank for which a displaced worker is qualified in a new occupation is limited by her scarce skill. As a result, larger changes in skill *composition* entail larger reductions in job *rank*, and hence larger reductions in earnings.

The model also makes two predictions that to the best of our knowledge are new. First, holding constant skill composition, workers displaced from more highly ranked positions will tend to suffer larger reductions in hierarchical rank. Empirical evidence consistent with this prediction has already been provided by Garg (2016), who finds that workers displaced from more highly ranked jobs as measured by their place in the occupational wage distribution (Autor and Dorn, 2014) tend to move to jobs of lesser rank, while workers displaced from lower-rank jobs tend to find jobs of *higher* rank. Of course, such mean reversion is consistent with other stories, including pure measurement error or serendipity. However, the model makes a second, stronger prediction: the effects of skill composition changes are more negative for workers displaced from more highly ranked jobs. The interaction of lost job rank with changes in the skill composition of jobs is not so readily explained with the measurement error or serendipity stories.

We test the implications of the model using data on full-time workers from the 1994-2018 Displaced Workers Surveys. As just alluded, we identify the job rank occupied by a worker as the place of the worker's occupation in the wage distribution (Autor and Dorn, 2014). We determine the composition of skills using information on each occupation's job task content, taken from the Dictionary of Occupational Titles. The angle between the task content vectors in different jobs emerges as a natural measure of the change in skill composition (Gathmann and Schönberg, 2010). We also attempt to identify the causal effects of – that is, account for the endogeneity of – skill composition changes, which to our knowledge has not been attempted in the displaced worker literature. We do so by using as instruments the occupation-specific means for *non-displaced* workers. We also find that the causal effects of changes in job task content are similar for displaced and non-displaced workers. Finally, we show that the changes in job rank translate into changes in earnings.

The paper is organized as follows. Section 2 introduces our measure of hierarchical rank. Section 3 introduces our measure of changes in skill composition. Section 4 presents our heuristic model. Section 5 presents our regression evidence and estimated effects. We consider how changes in hierarchical rank translate into changes in earnings in Section 6. Section 7 considers whether workers displaced from highly ranked jobs try to avoid large changes in skill composition. Section 8 concludes the paper with a brief summary, caveats, and suggestions for future research.

2 Job Rank Transitions

In their study of careers within a large firm, Baker et al. (1994) argue that hierarchical rank is "central to internal labor market descriptions of wage determination." However, given the role of promotions in motivating worker effort, one would expect hierarchical rank to play a role in movements of workers across firms as well as movement within the firm. For example, Lazear and Rosen (1981) model promotions an an incentive scheme when output or effort cannot be observed directly, but in which it is possible to make comparisons between workers. Firms tend to promote from within rather than hire externally to preserve incentives for low-rank workers, which could make it difficult for workers displaced from high-rank positions to find jobs at the same rank (Kwon and Milgrom, 2014, p.166).

2.1 Measuring Job Rank

Information on hierarchical rank is not readily available in the data sets most commonly used to study displaced workers. However, information on occupation *is*. Although the importance of occupation in the earnings outcomes of displaced workers is well known, the hierarchical notion of occupations has been little exploited. One exception is Forsythe (2017), who shows that the earnings changes of displaced workers are related to changes in job rank as measured using data on mean occupational wages. Another exception is Pung (2017), who finds a negative relationship between changes in occupational rank and rank of the lost job as measured by Autor and Dorn's (2014) measure of job skill, namely, the place of the occupation in the wage distribution.[1]

In this paper, we interpret the occupational wage percentile, conditioned on a host of individual-level characteristics, as a measure of its hierarchical rank.[2] We begin by estimating a log wage equation using data from the March Current Population Surveys as a function of schooling, potential labor market experience, demographic controls, a vector of 3-digit IPUMS (1990) industry dummy variables, and a vector of 3-digit IPUMS (1990) occupation codes.[3] Letting $\hat{\omega}_i$ denote the estimated coefficient on the indicator for occupation i, our measure of job rank is

$$RNK \equiv F(\hat{\omega}_i), \tag{1}$$

where $F(\hat{\omega}_i)$ is the value of cumulative distribution function in the sample.

Table 1 lists the 20 highest- and lowest-rank IPUMS (1990) occupations that contain at least 20 displaced workers. Not unexpectedly, the top 20 occupations include chief executives, pharmacists,

[1]Pung (2017) was looking for, but found no evidence of employment polarization in the job transitions of displaced workers.

[2]Other authors who have done so include Forsythe (2017), Groes et al. (2014), and Lazear (1992).

[3]We use the IPUMS occupation (1990) codes in order to sidestep the difficulty of estimating separate rank distributions for 3-digit and 4-digit Census occupation codes. We then match these IPUMS occupation (1990) effects back to the individual level data by calculating means by 3 or 4-digit Census occupation code. Because a few Census occupation codes match up to more than one IPUMS occupation code, weightings can differ between the displaced and non-displaced worker samples. For a handful of cases we expanded the set of IPUMS occupation (1990) codes to make the job rank measures between the displaced and non-displaced samples as similar as possible.

managers, and lawyers, and the bottom 20 occupations include food preparation workers, gardeners and groundskeepers, and taxi cab drivers. There are some surprises, with auto body repairers and butchers and meat cutters appearing in the top 20, and primary school teachers and teachers (not elsewhere classified) in the bottom 20.[4]

2.2 Current Population Survey Data

Like Poletaev and Robinson (2008) and Robinson (2018), we use data on displaced workers taken from the January (mostly) and February (sometimes) supplements of the Current Population Survey (CPS) (Sarah Flood and Warren, 2017). We focus on those who are employed full time as of the survey date, because Farber (2017) found that most earnings losses suffered by full time job losers result from a loss of hours worked, and that the average reduction in weekly earnings among displaced workers who are newly employed in full-time jobs are small by comparison with the losses of workers who are newly employed in part-time jobs.[5] We therefore start our analysis with 1994, the first year in which it is possible to identify such workers, and end with the 2018 sample year.

Like Robinson (2018), we make extensive use of a comparison sample of non-displaced workers using the monthly CPS data. The first sample uses data on rotations 2-4 and 6-8, for which the Census Bureau uses dependent coding procedures for occupation to reduce spurious switches, referred to as the "rank sample." The analysis of earnings limits us to respondents in the outgoing rotations (4 and 8), called the "earnings sample," and precludes us from using dependently coded occupation data.

2.3 Rank Change Patterns Among Occupation Switchers

This goal of this paper is to understand the role of lost job rank and changes in skill composition in the earnings outcomes of displaced workers. Because displaced workers who find jobs in the same occupation experience, by definition, no change in job rank, we examine patterns of rank change for workers who switch occupation.

Table 1 reports mean changes in rank for occupation switchers for the 20 highest- and lowest-rank occupations. Starting at the high end, workers who lost chief executive and public administration positions, $RNK = 100$, experience a mean decline in rank of 27 percentile points, and workers displaced from marketing and advertising managerial positions, a mean decline of 34 points overall, and a slightly higher 38 points for those displaced due to plant closure. The largest percentile point declines, 49 and 51 points, are found for grinding and related workers ($RNK = 98$). At the low end of the rank distribution, occupational switchers displaced from child care occupations ($RNK = 2$) experience mean *increases* of 28 and 37 percentile points, and those displaced from teaching, n.e.c. positions ($RNK = 3$), 55-56 points.

The data in Table 1 suggest that occupation switchers displaced from highly ranked occupations tend to find new jobs lower in rank, and those who are displaced from low-rank occupations tend to find new jobs higher in rank. Table 2 sheds somewhat more direct light on this question, showing 20 lowest and highest ΔRNK occupations. In addition to teachers n.e.c., occupations with the

[4] Compensating differences for risk seem relevant for the former two. The minimum rank equals 2 because lower-ranked occupations contained fewer than 20 displaced workers.

[5] In addition, the loss of earnings among workers who are *voluntarily* employed part-time are small compared with the loss of those who are involuntarily employed in part-time jobs. He also reports evidence that the transition to part time employment is voluntary, especially among those who lost long-term (more than 20 years of tenure) jobs.

largest mean increases in rank include guards and watchmen ($RNK = 9, \Delta RNK = 51$), door-door and kindred sales workers ($RNK = 3, \Delta RNK = 47, 38$), and truck and delivery drivers ($RNK = 13, \Delta RNK = 39, 37$), where the second number reported refers to those displaced due to plant closure. Occupations with the largest mean *decreases* in rank include butchers ($RNK = 97, \Delta RNK = -37$), licensed practical nurses ($RNK = 96, \Delta RNK = -35, -55$), and bill and account collectors ($RNK = 75, \Delta RNK = -32, -38$).[6]

Across 673 3 and 4-digit industries, the correlations reinforce the impression from Tables 1 and 1 that there is, indeed, a negative relationship between ΔRNK and RNK on the lost job, equal to -0.78 for displaced workers as a whole, and -0.71 for those displaced due to a plant closure. This relationship is visualized in Figure 1.

Finally, it is instructive to examine the means for non-displaced workers who switch occupations in column 5, and for the subset who switch employer, who are arguably more comparable with displaced workers, seen in column 6. As can be seen, they are remarkably similar to those of displaced workers. Although the circumstances of separation from the job may differ, it seems likely that similar economic forces are at work in terms of workers' subsequent decisions.

2.4 Interpreting Mean Reversion in Occupational Rank

The data indicate strong reversion to the mean in occupational rank between the lost and new job. The question naturally arises why it occurs. One possibility, not terribly interesting from an economic perspective, is that it results from measurement error or due to pure serendipity. In this paper, we argue that it follows from the task specificity of human capital. It is of prime importance, then, to distinguish between these two classes of explanations. In this paper, we will present a heuristic model that makes a prediction that follows naturally from the task specificity of human capital, and is difficult to reconcile with the measurement error or serendipity stories: lost job rank interacts negatively with changes in skill composition, reducing the rank of the new job.[7]

3 Measuring Changes in Skill Composition

3.1 Angular Separation

Before turning to the model, it is helpful to introduce our measure of changes in skill composition. In our heuristic model below, output is produced by combining a given set of skills in combinations that are specific to the firm. Progressing along a career path entails acquiring increasing levels of those skills in fixed proportion, while displacement entails moving to a new job at a new firm that employs those skills in a different proportion.

It will be seen that Angular Separation (Gathmann and Schönberg, 2010) emerges as a natural measure of skill composition change. Let S_{li} and and S_{ci} denote levels of the ith skill component required in the lost and current job. $i = 1, ...I$. The cosine measure of similarity between the two

[6] In most cases, the mean changes in rank for displaced workers as a whole and for those displaced due to a plant closure are of the same order. There are, however, exceptions: pharmacists ($RNK = 99, \Delta RNK = -29, -6$), lawyers ($RNK = 88, \Delta RNK = -31, -5$), and, at the other end, architects ($RNK = 19, \Delta RNK = 31, 2$). We leave investigation of the reasons for these discrepancies for future research.

[7] We recognize that errors in measurement can be a problem, such as in the measurement of earnings (Farber, 2017). The relevant question is whether such errors are sufficient to explain *all* of the patterns in the data.

jobs is equal to

$$\cos\theta \equiv \frac{\sum_{i=1}^{I} S_{li} \times S_{ci}}{\left(\sum_{i=1}^{I} S_{li}^2\right)^{1/2} \left(\sum_{i=1}^{I} S_{ci}^2\right)^{1/2}}, \tag{2}$$

which equals unity if occupations have identical skill content and equals zero if two occupations use entirely different skill content. Transforming Equation 2 into degrees yields the Angular Separation between the skill vectors,

$$ANGL_{cl} \equiv \arccos\theta \times 180^\circ/\pi, \tag{3}$$

which ranges from 0° to 180°.[8]

3.2 Euclidean Distance versus Angular Separation

Most prior research (Kwon and Milgrom, 2014; Poletaev and Robinson, 2008; Robinson, 2018) measures changes in skill composition using the Euclidean distance, equal to

$$D_{cl} \equiv \left[\sum_{i=1}^{I} [S_{ci} - S_{li}]^2\right]^{1/2}. \tag{4}$$

where S_{ji} denotes the value of the ith skill component in the lost (l) or current (c) job $j = l, c$. To see the difference between D_{cl} and $ANGL_{cl}$, suppose that there are just two skills, A and B. Consider a worker who is displaced from a job requiring skills in quantities A_1 and B_1 to a job 2 requiring the same amount of skill B, but a lower amount of skill A, $A_2 < A_1$. With the aid of Figure 3, it can be seen that the Euclidean distance is equal to

$$D_{cl} = |A_2 - A_1| = |\ell_2 \cos\theta_2 - \ell_1 \cos\theta_1|, \tag{5}$$

where ℓ_1 is the Pythagorean length of the skill vector in the lost job and ℓ_2 is the length of the skill vector on the new job. The Euclidean distance is equal to the weighted difference between angles that the skill vectors on the lost and current job make with the horizontal axis, θ_1 and θ_2, where the weights are the lengths of the respective skill vectors, ℓ_1 and ℓ_2.

In our heuristic model, it will be seen that the lengths of the skill vectors are indicative of the ranks of the two jobs, and so that the Euclidean distance combines two distinct forces: changes in the combination in which skills are used, and changes in job rank. This can be seen in a less formal way by noting that one way researchers commonly employ to capture the effects of changes in the skill level of the job on earnings (Robinson, 2018) is to construct a measure of skill defined as the weighted sum of the S_i,

$$Skill_j \equiv \sum_{i}^{I} \hat{\beta}_i S_{ji}, \tag{6}$$

where $\hat{\beta}_1, ...\hat{\beta}_I$ is a vector of positive weights estimated from an auxiliary wage regression, and $j = c, l$. Clearly, job 2 is less skilled than job 1 as measured by Equation 6, since $A_2 < A_1$ and the $\hat{\beta}_i$ are positive.[9]

[8]Gathmann and Schönberg (2010) measured the change in career trajectory as 1- $\cos\theta$, which is satisfactory when the s_i are uniformly positive, but in our case are factor scores that are centered on zero.

[9]Robinson (2018) called Equation 6 the "direction" of skill change. Modifications exist, for example, weighting the

3.3 Dictionary of Occupational Titles Data

Following Robinson (2018), we match the individual-level data in the Current Population Survey to occupation-level measures of skill content taken from the most recent (1991) Dictionary of Occupational Titles (DOT), which contains information on nearly 50 job characteristics for more than 400 1990-era 3-digit Census occupations.[10] The characteristics we use include 11 aptitudes (e.g., intelligence, verbal, numerical, spatial); 7 skill measures (e.g., general educational development, specific vocational preparation, nature of human interaction, use of data); 20 activity indicators (strength, climbing, reaching, vision); and 11 temperament indicators (e.g., take/follow direction, repetitiveness of the job, stress).

Like Poletaev and Robinson (2008) and Robinson (2018), we use factor analysis to reduce these nearly 50 characteristics into 5 skill factors, denoted S_i, $i \in [1, 5]$, rotated using the varimax method, using the March CPS data.[11] The first factor loads most heavily on reasoning, intelligence, and math skills. Three of the factors loaded heavily on physical tasks: kneeling, crouching and climbing (2), motor skills and finger dexterity (3), and vision, acuity, and coordination (5). The fourth factor loaded most heavily on talking, hearing, and people skills. The DOT scores are then matched to the individual-level Current Population Survey data by 3-digit (1990s) and 4-digit (2000s and 2010s) occupation.[12]

3.4 Skill Composition Changes: Data Overview

Across 760 3- and 4-digit occupations, the unweighted mean value of $ANGL$ among displaced workers as a whole is 69.9. To put this in perspective, Table 3 contains mean values of $ANGL$, conditional on switching occupation – $ANGL$ is by definition zero for non-switchers – for the top and bottom-20 (ranked using displaced workers as a whole) 3-digit IPUMS (1990) occupations. Among displaced workers as a whole (column 1), the largest changes in career trajectory were incurred by computer and peripheral equipment operators (100 degrees), followed by production supervisors (97 degrees), guards and watchmen (93), payroll and timekeeping clerks (91) and teachers not elsewhere classified (89). The smallest changes in career trajectory average were incurred by chief executive officers and public administrators (32), managers of service organizations (36), engineers not elsewhere classified (49), and financial managers (41).

squared skill difference by the β_i so as to place more weight on factors that have greater impact on earnings. Robinson (2018) dealt with the ambiguity of the Euclidean distance measure by renormalizing vector lengths. We will see that the Angular Separation measure is more readily interpretable within our heuristic model. Finally, the reader may wonder why we did not define job rank as the Euclidean length of the 5-vector $S_1, ..., S_I$. Empirically speaking it falls short. First, the various elements explain relatively little of the variation in log earnings, either in an absolute sense or when compared with the occupational wage percentile. Second, neither DOT characteristics nor their factors have a natural metric, so changes in the length of the Euclidean vector are not readily interpretable. Third, historically, the DOT was developed during the 1930s to help the new public employment system improve linkages between supply and demand (Sommers et al., 1993) and more recently has been described as "mainly ... an aid to low-stakes decision processes such as vocational counseling, career guidance, job referral, and job placement"(Handel, 2015) – not to measure a worker's place in the firm's hierarchy.

[10] We are grateful to Christopher Robinson (Robinson, 2018) for supplying us with the DOT data by 3-digit 1990-era Census occupation along with detailed instructions for matching them to the CPS data.

[11] In other words, we carry out the factor analysis on DOT-augmented individual-level data from the March 1994-2018 surveys, applying the supplement weight.

[12] We followed the instructions in Robinson (2018) for matching the DOT data to 2000- and 2010-era 4-digit Census occupation codes, using the dual-coded monthly CPS data available for January 2000 through December 2002 and taking averages by era-2000 occupation code and gender.

As might be expected, the figures for those displaced due to a plant closure, seen in column 2, are similar to those in column 1. The unweighted mean across the same 760 occupations is nearly identical, equal to 69.0, and the unweighted pairwise correlation is 0.67, rising to 0.80 when weighted by the number of displaced workers. More surprising is the similarity of the means of $ANGL$ for non-displaced workers, equal to 66.7 (column 3) and 66.8 (non-displaced workers who switch employer as well as occupation, seen in column 4).[13] Across 746 common 3- and 4-digit occupations, the pairwise correlation between the means is 0.47 for displaced workers and non-displaced workers as a whole (a visual representation is seen in Figure 2) and 0.40 for displaced workers as a whole and non-displaced employer switchers. The same two correlations for those displaced due to plant closure are 0.35 and 0.31.[14]

4 Heuristic Model of the Effects of Displacement

Workers who are displaced face a crucial decision of where and how long to search for new employment. Lazear (2009) notes that the change in productivity associated with a change in firm depends on the thickness of markets. The wage loss associated with involuntary turnover is smaller when there is a thicker market for the particular combination of skills used by the worker. In addition, he observes that there are more entry jobs low down in a job hierarchy, and fewer high up, and hence workers displaced from higher ranked jobs will therefore tend to experience larger wage losses.

It is beyond the scope of this paper to examine the availability of jobs of particular skill compositions in different labor markets. Rather, our purpose is to model and examine empirically the consequences for displaced workers of choosing jobs with different skill compositions. In our model, what is specific to the firm is not the type of human capital acquired, but the combination in which various skills are used, called the task-specific approach to human capital (Gibbons and Waldman, 2004; Lazear, 2009). Each job is characterized by (1) the composition of skills used and (2) hierarchical rank. As will become clear, the ability to transfer human capital post-displacement is limited by the "scarce" skill, so that larger changes in skill *composition* entail larger reductions in job *rank*, and hence earnings.

4.1 Production and Skill Composition

Like Lazear (2009), we assume that different firms use two distinct skills, A and B, in different proportions. The algebra is much simplified by assuming that A and B are perfect complements, so that the output q_{ij} produced in a job i at a firm j equals

$$q_{ij} = \min[A_i, \alpha_j B_i], \tag{7}$$

[13] Robinson (2018) also finds differences in skill composition changes evolution between displaced and non-displaced workers. He also finds that the mean distance in occupational mobility following displacement declined significantly in the 1980s and 1990s, which he interprets as evidence of more efficient job matching.

[14] Keep in mind, too, that the figures for non-displaced workers use month-to-month data, while the figures for displaced workers reflect periods of between one and three years.

where $\alpha_j > 0$.[15] Equation 7 implies that within a firm j, career progression consists of acquiring additional amounts of skills A and B in fixed proportion, so that in any job i, we have

$$A_i = \alpha_j B_i \quad \forall i, \tag{8}$$

and so a career trajectory within a firm takes the form of a straight-line path radiating from the origin, with α_j units of skill A for each unit of skill B. Notice that the potential for advancement is independent of α_j, and requires simply acquiring increasing amounts of skills A and B in the indicated proportion. Equations 7 and 8 embody the notion of Gibbons and Waldman (2004) that firms design careers so as to minimize the loss in human capital acquired along the way (205).[16]

4.2 Effects of Career Trajectory Change: The Basic Insight

The consequences of displacement are seen in Figure 3. We consider an individual who is initially employed in job 1, with $q_1 = \min[A_1, \alpha_1 B_1]$. Her career path is given by the straight line through the origin, which makes angle θ_1 with the horizontal axis, which we refer to as her *career trajectory*.

If the worker is displaced from her job and finds a new job along the same career trajectory, her output is unchanged. Suppose, however, that she is only able to find a new job in a firm that uses $\alpha_2 < \alpha_1$ units of skill A for every unit of skill B. Because career trajectory 1 entailed acquiring large amounts of skill A relative to skill B, and because $\alpha_2 < \alpha_1$, her output at the new job along career trajectory 2 equals

$$q_2 = \min[A_2, \alpha_2 B_1] < q_1, \tag{9}$$

where we have used the fact that $A_1 - A_2$ units of skill A are unproductive in the new job. As can be seen, her output on the new job is limited by the amount of her scarce skill B. And if she is unable to find a new job along career trajectory 2 but can find a new job along career trajectory 3, her output will fall even farther to $q_3 = \min[A_3, \alpha_3 B_1] < q_2 < q_1$.

Evidently, the worker's output on the new job declines by more, the larger the difference in α. It is unclear, however, how to apply this insight to the data because it is not clear how to capture α in the data.[17] Notice, though, that $\theta_j \equiv \tan^{-1}(1/\alpha_j)$, and the change in α is directly related to

$$ANGL_{12} = \Delta\theta_{12} = \theta_2 - \theta_1, \tag{10}$$

which is nothing more than our Angular Separation measure of skill composition change.

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[15] The assumption that A and B are perfect complements is not essential, but simplifies the exposition. Lazear (2009) allows for perfect substitutability between the two skills, but investment is still unbalanced, and workers who switch career trajectories still incur a loss.

[16] Gibbons and Waldman (2004) describe their approach as "the simple but plausible idea that much of the human capital accumulated on the job is due to task-specific learning by doing" (203). Thus, for example, to the extent that career advancement consists of being promoted to a supervisory position, supervisors will have once performed the task of the workers being supervised. Skills useful in performing higher-level jobs would tend to be incorporated in low-level jobs that feed into that high-level job (206). The reader may wonder whether career paths in the real world converge or intersect at higher ranks. In this case, workers displaced from higher ranks could incur *smaller* changes in job task content than lower-rank workers, and such changes could be less costly. Ultimately, the question is empirical. That workers displaced from higher-rank jobs tend to experience greater reductions in rank in the new job (Section 2.3) suggests that our assumptions are not implausible. That said, it is interesting that Murphy (1986) shows in a 2-skill model of lifetime investment under uncertainty and unequal initial endowments, the optimal skill paths of individuals will in general never cross (111).

[17] Even were one to believe that the production technology were truly Leontief, implementation is problematic because the various skill elements in the Dictionary of Occupational Titles are measured using different scales, and reduced to 5 extracted factors.

Definition 1 (Defining Occupational Rank) Recall that our empirical overview in Section 2 focuses on changes in the worker's job rank as measured by the place of her occupation in the wage distribution. Although nothing prevents us from identifying output q_{ij} with job rank, it is more convenient to work in terms of the Euclidean length of the skill vector than output itself, ℓ. With reference to Figure 1, rank on job 1 is therefore equal to

$$\ell_1 = ({A_1}^2 + B_1^2)^{\frac{1}{2}}. \tag{11}$$

All jobs along a circle with diameter ℓ_1 across different career trajectories correspond to the same job rank.[18]

We are now ready to explore the implications of this simple model.

Implication 1 (Changes in Career Trajectory Reduce Job Rank) Workers who change career trajectories will be employed in a job with a hierarchical rank lower than the one from which they were displaced. By elementary trigonometry, $B_j = \ell_j \sin\theta_j$, so the ratio of the ranks on a new job along career trajectory 2 and the lost job equals

$$\frac{\ell_2}{\ell_1} = \frac{\sin\theta_1}{\sin\theta_2} < 1. \tag{12}$$

Although Equation 12 shows that the *ratio* of the career ranks on the lost and new job are independent of the rank of the lost job, our next implication shows that the *arithmetic difference* is *not*.[19]

Implication 2 (Effect of Lost Job Rank on New Job Rank) The change in hierarchical rank, $\Delta\ell \equiv \ell_2 - \ell_1$, is negatively related to the rank of the lost job. Subtracting 1 from both sides of Equation 12 and rearranging yields

$$\Delta\ell = \ell_1 \left(\frac{\sin\theta_1}{\sin\theta_2} - 1 \right). \tag{13}$$

Taking the partial derivative of Equation 13 with respect to ℓ_1, we have

$$\frac{\partial\Delta\ell}{\partial\ell_1} = \frac{\sin\theta_1}{\sin\theta_2} - 1 < 0 \tag{14}$$

The result is illustrated in Figure 4, where we compare two workers originally on career trajectory 1, one of whom loses a high-rank job, $\ell_{1,hi}$, and the other a job of low rank, $\ell_{1,lo}$. The ranks of the new jobs along career trajectories 2 and 3 are given by the lengths of the solid lines for the worker who lost the low-rank job, and by the lengths of the dashed lines for the worker who lost

[18] By definition, $\ell_1 = B_1(1 + \alpha_1^2)^{1/2} = q_1(\alpha_1^{-2} + 1)^{1/2}$, so holding constant α, $\partial\ell_1/\partial q_1 = 1$.

[19] In Lazear's (2009) model, tasks A and B are perfect substitutes. The main point remains intact: Changes in career trajectory entail reductions in job rank. The basic point can be made by assuming no exogenous quits, assuming that workers place zero probability on the event that they lose their job involuntarily, and equal quadratic costs of skill acquisition. In his notation, we assume that the costs of skill acquisition are $C(A) = A^2, C(B) = B^2$. Let output on job 1 be $Q_1 = (4/5)A + (1/5)B$ and output on job 2, $Q_2 = (1/5)A + (4/5)B$. Then carrying out the maximization in his equation 2 on page 920, $A^* = 4/5$, $B^* = 1/5$, and $Q_1^* = 17/25$. If the worker unexpectedly loses their job and can only find work in a job of type 2, $Q_2^* = 8/25$. Allowing for small probabilities of quits will not change the basic story. Larger changes in job type entail larger losses. Imperfect substitutability can be modeled similarly.

the high-rank job. Implication 2 shows that for displacement from career trajectory 1 to career trajectory 2, $|\ell_{2,hi} - \ell_{1,hi}| > |\ell_{2,lo} - \ell_{1,lo}|$. The same holds for displacement to career trajectory 3.

Our next implication addresses the effect of skill composition. We have defined career trajectories in terms of the angle θ that they make with the horizontal axis. The magnitude of the change in skill composition is therefore directly related to the difference in θ between the lost and new jobs. Without loss of generality, we take θ_1 as fixed, and consider the effects of changes in θ_2.

Implication 3 (Effect of Changes in Skill Composition) The change in job rank is negatively related to the magnitude of skill composition change. Partially differentiating Equation 13 with respect to $\sin\theta_2$ yields

$$\frac{\partial \Delta\ell}{\partial \sin\theta_2} = -\ell_1 \frac{\sin\theta_1}{\sin^2\theta_2} < 0, \tag{15}$$

where we use the fact that $\partial \sin\theta_2/\partial\theta_2 > 0$. This result is illustrated in Figure 3, where we consider a worker initially employed along career trajectory 1 in a job of rank ℓ_1, and compare the effect on job rank of moving to career trajectory 3 with the effect of a move to career trajectory 2, with $\theta_3 > \theta_2 > \theta_1$. It is clear in the Figure that $\ell_3 < \ell_2$, and that $\ell_3 - \ell_1 < \ell_2 - \ell_1$.

The next Implication follows immediately from Equations 14 and 15.

Implication 4 (Skill Composition Change and Lost Job Rank Interact) The effect of changes in skill composition on the change in job rank is more negative, the higher the rank of the lost job. Partially differentiating Equation 15 with respect to ℓ_1 yields

$$\frac{\partial^2 \Delta\ell}{\partial \sin\theta_2 \partial\ell_1} = -\frac{\sin\theta_1}{\sin^2\theta_2} < 0. \tag{16}$$

The result can be visualized by returning to Figure 4. Noting that Equation 16 concerns a difference-in-difference, we compare the effects of changes in θ on $\Delta\ell$ for two workers initially employed along career trajectory 1, one in a high rank job and one in a low rank job. The effect of an increase in θ on the new job from θ_2 to θ_3 is given by $(\ell_3 - \ell_1) - (\ell_2 - \ell_1) = \ell_3 - \ell_2$. It is visually obvious that $|\ell_{3,hi} - \ell_{2,hi}| > |\ell_{3,lo} - \ell_{2,lo}|$, implying $\ell_{3,hi} - \ell_{2,hi} < \ell_{3,lo} - \ell_{2,lo}$.

Implication 4 is related to Gathmann and Schönberg's (2010) argument that because workers accumulate more task-specific human capital as they age, a distant occupational switch becomes more costly and so such moves will tend to occur earlier in life (9).

4.3 Upward Job Moves

Farber (2017) finds that a substantial fraction of displaced workers experience increases in earnings, and Pung (2017) finds that workers displaced from low-rank occupations tend to move to *higher* rank occupations. Both findings suggest that workers (1) acquire human capital on the job and (2) are not always employed in jobs that make full use of their skills. One reason is that search and job switching are costly (Farber, 2017). A second reason is that promotion may be delayed to avoid the consequences of the Peter Principle (Lazear, 2004b).[20] We attempt to address these facts by adding two refinements to our heuristic model.

[20]In particular, if firms promote workers who perform at or above some standard, randomness in performance means that workers who satisfy the promotion criterion at one point in time may have done so "purely by chance," and it is likely that their subsequent performance will revert to the mean. Firms can increase the chance of promoting

Refinement 1 (Human Capital Accumulation) A worker in job i working in firm j acquires human capital on the job at rate $h(\ell_{ij}) \geq 0$ that depends negatively on job rank ℓ_{ij}. Let the skill levels in job i start at A_i, B_i. The increment to human capital is then equal to

$$\Delta A_i = \alpha_j \Delta B_i = h(\ell_{ij}) A_i = \alpha_i h(\ell_{ij}) B_i > 0, \tag{17}$$

with $h(\ell) \geq 0$, $h'(\ell) \leq 0$, and where we assume

$$\frac{\partial \Delta B_i}{\partial \ell_{ij}} = \frac{\partial h(\ell_{ij}) B_i}{\partial \ell_{ij}} = \sin\theta \frac{\partial h(\ell_{ij}) \ell_i}{\partial \ell_{ij}} < 0, \tag{18}$$

that is, the increment to human capital declines with rank.[21]

Refinement 2 (Delayed Promotions) Workers are not always be employed in tasks that make full use of their human capital. To be concrete, we assume that the worker along career trajectory j who was employed in lost job i of rank ℓ has $A_i(1 + h(\ell))$ and $B_i(1 + h(\ell))$ units of skills A and B at the time of displacement. We assume further that

$$\frac{\partial B_i(1 + h(\ell_i))}{\partial B_i} > 0, \tag{19}$$

meaning that the stock of human capital is increasing in the rank of the job currently occupied by the worker.

4.4 Limitations on Human Capital Transferability

We now consider two limitations on human capital transferability. First, the personnel economics literature suggests that workers who lose highly ranked jobs could have difficulty finding a new job at the same rank because such lateral re-entry could interfere with the promotion incentives of existing workers. Second, some portion of the worker's human capital could be truly specific to the firm in which they worked.[22] These concerns lead us to build into the model a limitation on the transferability of human capital.[23]

truly high-ability workers by delaying promotion until they acquire more data. Other explanations are possible. For example, financially stressed firms may be less likely to promote workers. Indeed, Haltiwanger et al. (2018) found that workers are more likely to be promoted during economic expansions than during contractions (1.21% versus 0.73% per quarter), "driven primarily by a decline in the probability of moving out of the bottom rung, conditional on moving, rather than from impacts in the overall mobility rate" (79). Regardless of the state of the economy as a whole, firms that are on the verge of shutting down are probably less likely to promote workers. Even so, the costliness of job search could cause workers to be reluctant to give up their "place in line" and hence stay with the firm even with lower odds of being employed. In addition, being separated from a firm involuntarily arguably puts workers who do eventually lose their job in a stronger position to signal that they were not separated for cause.

[21] $\partial h(\ell_{ij}) B_i / \partial l = h(\ell) \partial B_i / \partial \ell_{ij} + B_i \partial h(\ell_{ij}) / \partial \ell_{ij}$, equal to the sum of a positive and negative term, with the negative term assumed to dominate, but not so much as to cause $\Delta B_i < 0$.

[22] A number of authors have argued that promotions and specific human capital investment are complementary. For example, Prendergast (1993) shows that promotions can be used to induce workers to invest efficiently in specific human capital. The model of Scoones and Bernhardt (1998) allows workers to invest in both firm specific and general human capital, the difference being that general human capital increases their value outside the firm. The incentive to invest in specific human capital is maintained by the fact that it is costly for outside firms to obtain information. Empirically speaking, Kwon and Milgrom (2014) infer that the significance of firm- and occupation-specific human capital rise with hierarchical job rank in their study hiring and promotion using Swedish data.

[23] We ignore here the possibility that the Peter Principle plays a role (Lazear, 2004a). Promoted individuals' performance falls, on average, relative to their performance prior to promotion because performance contains both a

Refinement 3 (Limits on Human Capital Transferability) Let ℓ denote the potential rank of the worker absent incentive concerns or in the presence of full transferability of human capital. We assume that the actual rank of the displaced worker in the new job equals $\ell_a = \phi\ell$, where $0 < \phi \leq 1$.[24]

We consider now how these three refinements affect the implications of the heuristic model.

Implication 5 (Job Rank Can Rise (Decline) for Career Switchers (Stayers)) Refinements 1 and 2 make it possible for workers who lose low-rank jobs to experience increases in job rank, while Refinement 3 makes it possible for workers who remain on the same career trajectory to experience reductions in job rank. The ratio of new and lost job ranks now equals

$$\frac{\ell_a}{\ell} = \phi(1 + h(\ell))\frac{\sin\theta_1}{\sin\theta_2}, \tag{20}$$

which can be greater than, equal to, or less than unity as

$$1 + h(\ell) \lesseqqgtr \frac{\sin\theta_2}{\sin\theta_1}\frac{1}{\phi}. \tag{21}$$

Equations 20 and 21 tell us that displaced workers can find a job at higher rank when human capital investment is high, which will tend to be earlier in the career at lower lost job rank. They also show that a displaced worker who finds a new job along precisely the same career trajectory can still experience a decline in job rank if the lateral entry penalty is high, that is, if ϕ is low.

Implication 6 (The Comparative Statics Are Unaffected by the Refinements) Subtracting unity from Equation 20 and multiplying by ℓ, the change in rank between the lost and new job now equals

$$\Delta\ell = \ell_a - \ell = \ell\left(\frac{\sin\theta_1}{\sin\theta_2}\phi - 1\right) + \phi\ \ell h(\ell)\frac{\sin\theta_1}{\sin\theta_2}, \tag{22}$$

where we observe that the proportionality of the penalty causes the *magnitude* of the penalty to be larger for workers who lose higher-rank jobs. Differentiating Equation 22 with respect to ℓ yields

$$\frac{\partial\Delta\ell}{\partial\ell} = \left(\frac{\sin\theta_1}{\sin\theta_2}\phi - 1\right) + \phi\ \frac{\partial h(\ell)\ell}{\partial\ell}\frac{\sin\theta_1}{\sin\theta_2} < 0. \tag{23}$$

Both right-hand-side terms are unambiguously negative, the second due to the assumption that human capital investment declines in job rank (Equation 18). Differentiating Equation 23 with respect to $\sin\theta_2$ yields

$$\frac{\partial^2\Delta\ell}{\partial\sin\theta_2\partial\ell} = -\phi\frac{\sin\theta_1}{\sin^2\theta_2}\ \left(1 + \frac{\partial h(\ell)\ell}{\partial\ell}\right), \tag{24}$$

permanent and transitory component. Reversion to the mean occurs because positive readouts on performance prior to promotion are uncorrelated with the readout after promotion (S143). Part of this can occur if workers are gaming a tournament scheme, in which they may produce more prior to promotion than afterward.

[24] To see that this formulation fits for firm-specific human capital, let q_k denote potential output at new firm k absent firm specificity. Assume that $\phi_a < 1$ and $\phi_b < 1$ are the fractions of skills A and B that are transferable. Then actual output will be $q_{ak} = \min[\phi_a A, \alpha_k\phi_b B] = \phi\min[A, \alpha_k B] = \phi q_k$, where $\phi = \min[\phi_a, \phi_b]$. Then observe that $\ell_a = q_{ak}(\alpha^{-2} + 1)^{1/2} = \phi q_k(\alpha^{-2} + 1)^{1/2} = \phi\ell$.

which is negative because the term in parentheses is equal to

$$\frac{\partial \ell}{\partial \ell} + \frac{\partial h(\ell)\ell}{\partial \ell} = \frac{\partial \ell(1+h(\ell))}{\partial \ell} = \frac{\partial \sin\theta_1 \ell(1+h(\ell))}{\partial \sin\theta_1 \ell} = \frac{\partial B_1(1+h(\ell))}{\partial B_1} > 0,$$

the term being unambiguously positive by assumption (see Equation 19).

4.5 Differences in the Potential for Advancement Across Trajectories

Finally, we have assumed until now that the potential for career advancement is equally possible along every career trajectory. In reality, few welders advance to vice president of the construction company by acquiring ever more sophisticated welding skills. Rather, they must acquire a mix of skills more heavily weighted towards analytic, business, and inter-personal skills. Figure 5 portrays the case in which career advancement requires acquiring a mix of skills weighted increasingly heavily towards B. The maximum rank achievable along any career trajectory is indicated by the solid lines. Thus, the maximum rank achievable along career trajectory 1 is ℓ_1. Advancement as far as rank ℓ_2 is possible along career trajectory 2, and to ell_3 along career trajectory 3.[25] This refinement affects Implication 3.

Implication 3A (Incentive to Change Career Trajectory) Low-rank workers may benefit by moving to jobs of different skill composition in order to advance their careers, while high-rank workers continue suffer from composition changes.

We now move to confront the predictions of our heuristic model with the data.

5 Regression Analysis of Job Rank Change

5.1 Specification

We test the key implications of our model with the regression equation given by

$$\begin{aligned} \Delta RNK_{ijk} = \beta^R_R LRNK_{ij} + \beta^R_A ANGL_{ijk} + \beta^R_{RA} LRNK_{ij} \times ANGL_{ijk} \\ + \beta^R_X X_i + \beta^R_S LSKL_{ij} + \epsilon_{ijk}, \end{aligned} \tag{25}$$

where ΔRNK_{ijk} is the change in job rank for an individual i who was initially employed in occupation j and is currently employed in occupation k, $LRNK_{ij}$ is rank on the lost job, $ANGL_{ijk}$ is the angular separation between the skill composition vectors on the lost and new jobs, X_i is a vector of control variables, and $LSKL_{ij}$ is the skill level of the lost job (see Equation 6). Although our overview of the data concentrated on workers who switch occupations, our regression analysis includes occupation stayers for whom $i = j$, in which case $\Delta RNK_{ijk} = 0$, and $ANGL_{ijk} = 0$.

[25] Frederiksen and Kato (2017), using Danish panel employer-employee data, find that there is a significant and positive relationship between the number of roles an individual has experienced in the labor market and the odds of career success as measured by the appointment to a top management position, with roles experienced internally being more important than externally obtained roles (23). They interpret their findings as indicating the importance of broadening of human capital (while acknowledging that there are competing interpretations). It is not clear whether the number of roles is indicative of moving up along a given career trajectory in our model, in which the proportion in which skills are used are the same, or across career trajectories that use skills in different proportions.

5.1.1 Testing the Predictions

Our model makes the following predictions:

- By Implication 2, the change in job rank is negatively related to the rank of the lost job. Partial differentiation of Equation 25 with respect to $LRNK_{ij}$ yields

$$\frac{\partial \Delta RNK_{ijk}}{\partial LRNK_{ij}} = \beta_R^R + \beta_{RA}^R \times ANGL_{ijk}, \tag{26}$$

  which will be negative provided that $\beta_R^R < 0$ and $\beta_{RA}^R < 0$.

- Implication 4 predicts that

$$\frac{\partial^2 \Delta RNK_{ijk}}{\partial ANGL_{ijk} \partial LRNK_{ij}} = \beta_{RA}^R < 0. \tag{27}$$

  Notice that this implies that Equation 26 is negative at all values of $ANGL_{ijk}$.

- According to Implication 3A, the effect of changes in skill composition, which is equal to

$$\frac{\partial \Delta RNK_{ijk}}{\partial ANGL_{ijk}} = \beta_A^R + \beta_{RA}^R \times LRNK_{ij}. \tag{28}$$

  may (but need not be) positive at low values of $LRNK_{ij}$, but will certainly be negative at high values. Thus, β_A^R can be either negative or positive, but $\beta_{RA}^R < 0$ is necessary to guarantee that Equation 28 be negative at high lost job rank.

Summarizing, then, the data will be consistent with our heuristic model provided that $\beta_R^R < 0$ and $\beta_{RA}^R < 0$, while β_A^R can be either positive or negative.

5.1.2 Endogeneity of Angular Separation: Problem and Solution

We take $LRNK_{ij}$, the rank of $i's$ lost job j, as exogenous. However, $ANGL_{ijk}$, equal to the angular separation between the occupational skill vectors of lost job j and current job k, is clearly a choice variable. The question then becomes what are the consequences of this fact.[26] One possibility is that a spurious negative relationship between ΔRNK_{ijk} and $ANGL_{ijk}$ could emerge. Suppose, for example, that less able displaced workers tend to draw more negative values of ϵ_{ijk}, meaning that they are more likely to move down in rank between the lost and current job, but may also for the same reason be less likely to find jobs that place similar weight on the particular combination of skills used on the last job, and hence tend to have higher values of $ANGL_{ijk}$. The result could be a spurious negative relationship between $ANGL_{ijk}$ and ΔRNK_{ijk}.

As explained in Section 3, our strategy for dealing with the endogeneity of $ANGL_{ijk}$ exploits the strong, positive correlation between occupation-level means of $ANGL_{ijk}$ for displaced and non-displaced workers.In particular, we use mean values by occupation of $ANGL_{ijk}$ and its interactions

[26] The issue of endogeneity is well known (Poletaev and Robinson, 2008; Robinson, 2018). One indication of endogeneity is that observed changes in job content are much smaller than would be observed under random mobility (Robinson, 2018). Robinson (2018) calculates that under random mobility, just 1.5% of male workers age 20-64 would remain in their current occupation, compared with the actual proportion of 40% (23). Just 29% of males exhibit short-distance changes in skill portfolio under random mobility, compared with 47% in the actual data.

for non-displaced workers as instruments for individual-level values among displaced workers, and means by occupation among displaced workers as instruments for the individual values of non-displaced workers.[27] Our first stage is therefore given by

$$\begin{bmatrix} ANGL_{ijk} \\ ANGL_{ijk} \times LRNK_{ij} \end{bmatrix} = \Gamma_X X_{ij} + \Gamma_R LRNK_{ij} + \Gamma_A \overline{ANGL_j} + \Gamma_{RA} \overline{ANGL_j \times RNK_j} + \Upsilon_i, \quad (29)$$

where over-lines indicate occupation-specific means of those variables calculated using the sample of non-displaced workers when worker i is displaced, and using the sample of displaced workers when worker i is not displaced.

5.1.3 Control Variables and Clustering

Our choice of control variables, X_{ij}, closely aligns with Farber (2017), and includes age, formal schooling, job tenure, years since displacement, other demographic controls, and dummy variables for survey year. The estimated effects of these control variables are for the most part unremarkable, and so we will not spend a great deal of time discussing them.

For the sake of completeness, and for purposes of comparison with the work of other researchers (Robinson, 2018), we include skill on the lost job, $LSKL_{ij}$, as a control variable.[28] We have, however, excluded its interaction with $ANGL_{ij}$, which entered with mixed sign and was never significant. Also for the sake of completeness, we will carry out a parallel examination of the change in job skill, replacing the dependent variable in Equation 25 with the change in job skill between the current and lost job, ΔSKL_{ijk}.

$ANGL_{ijk}$ varies at the 3- or 4-digit (depending on sample year) occupation level. However, $LRNK_{ij}$ varies at the 3-digit IPUMS occupation (1990) level, and so is the unit on which the standard errors are clustered.

5.2 Regression Results

Columns 1-3 of Table 7 contains selected coefficients and standard errors of two stage least squares estimates of Equations 25 and 29. We briefly examine some of the estimated effects of the control variables. First, the estimated coefficients on the tenure indicators for the lost job, available only for displaced workers, are all positive, indicating that job rank on the new job is between 1 and 2 percentile points higher for workers with higher levels of tenure than that of the omitted category (less than 1 year). Three of the four estimated tenure effects are higher for workers displaced due to a plant closure than for displaced workers overall.

5.2.1 Effects of Lost Job Rank

We use Equation 26 to estimate the effects of a standard deviation increase in lost job rank evaluated at low, medium, and high values of $ANGL$ – the mean minus, the mean, and the mean plus one

[27]The question naturally arises what determines these mean values, which is left for future research. The positive correlation of $ANGL$ between displaced and non-displaced workers suggests that the costs and benefits of taking certain career paths are similar. Put informally, the career trajectories of engineers or bank tellers who are displaced are not unrelated to the trajectories of those not displaced.

[28]Murphy (1986) shows that shadow prices for skills may not be equalized across sectors "due to the bundling restrictions implied by the embodied nature of human capital" (16). Thus Equation 6 will be an error-ridden measure of the true level of occupational skill. By contrast, our measure of job rank should encapsulate much more of the information about the market value of the *bundle* of skills used in an occupation, while admittedly sacrificing the ability measure the contribution of each element S_i to compensation, a task that we leave for future research.

standard deviation. Consulting the results for displaced workers as a whole, seen in column 1 of the first panel of Part A of Table 8, a standard deviation increase in lost job rank is predicted to change ΔRNK_{ij}, in percentile points, by

- -3.19 (s.e.=1.16) at low angular separation
- -14.44 (s.e.=0.42) at mean angular separation
- -25.70 (s.e.=1.18) at high angular separation

The estimated effects for workers displaced due to a plant closure are nearly identical, at -3.82 (1.52), -14.48 (0.52), and -25.14 (1.53).

The estimated effects for non-displaced workers, seen in column 3, are in the same direction, are are quantitatively similar (if somewhat smaller) in magnitude at -0.46 (0.04), -10.28 (1.53), and -20.10 (3.09) percentile points. These results are enticing because in the presence of "essential heterogeneity" – that is, if displaced workers and non-displaced workers were different in some essential way – one would expect these regressions to identify different underlying economic parameters. Although cannot make firm conclusions, the fact that the estimates are similar suggest that the underlying processes at work are not dissimilar.

5.2.2 Effects of Skill Composition

Consistent with Implication 4, $\hat{\beta}_3$ is negative. We see, too, that $\hat{\beta}_2$ is positive, which is consistent with the proposition that changes in skill composition benefit low-rank workers by permitting them to progress to higher ranks, but have negative consequences for high-rank workers (see Implication 3A). Again consulting the results for displaced workers as a whole in column 1 of Table 8, each standard deviation increase in $ANGL$, evaluated at low, medium, and high lost job rank, is predicted to change ΔRNK by

- +11.57 (s.e.=1.41) at low lost job rank
- +0.32 (s.e.=1.21) at mean lost job rank
- -10.94 (s.e.=1.83) at high lost job rank.

Again, the estimated effects for workers displaced due to a plant closing are similar at 11.01 (2.27), 0.35 (1.69), and -10.31 (2.16) percentile points.

Among non-displaced workers, the estimated effects are statistically indistinguishable from those of displaced workers at low and medium rank last jobs – we cannot say whether the job was "lost" – at 12.40 (1.64), 2.58 (1.76), and -7.23 (2.89) – at low, medium, and high rank last jobs. Certainly, the estimated effects for non-displaced workers are identified off of a much smaller fraction of job changers than those for displaced workers. Again, however, that the estimated effects are in of the same order of magnitude reinforces the impression that the forces operating are not dissimilar.

Our results are consistent with those of Robinson (2018), who finds that the effect of changes in skill composition are associated with lower earnings on the new job only when displaced workers find jobs at lower skill levels. Workers who lose low-rank jobs tend to experience *increases* in job rank on the next job, while those who lose high-rank jobs are estimated to experience rank decreases, and the effects of skill composition changes are higher for the former than the latter. Our results also go a bit farther, though, because they suggest that the effects of skill composition change are *positive* for workers of low job rank.

5.3 Regression Analysis of Job Skill Change

We next examine whether the same reasoning as applies to job rank applies to job skill. We replace the dependent variable in Equation 25 with ΔSKL_{ij}, and the interaction term with $ANGL_{ijk} \times LSKL_{ij}$. Selected estimated coefficients for these models are contained in columns 4-6 of Table 7. For workers displaced, the pattern of results is remarkably similar to that for changes in job rank. Consulting the results for displaced workers as a whole in column 4 of Table 8, each standard deviation increase in lost job skill is predicted to change $\Delta Skill_{ij}$, in percentile points, by

- -0.03 (s.e.=0.01) at low angular separation
- -0.10 (s.e.=0.01) at mean angular separation
- -0.16 (s.e.=0.01) at high angular separation,

and each standard deviation increase in angular separation, by

- +0.06 (s.e.=0.01) at low lost job skill
- -0.00 (s.e.=0.01) at mean lost job skill
- -0.07 (s.e.=0.01) at high lost job skill.

The magnitudes and precision of the estimated effects for workers displaced due to a plant closing are similar.

How do the results for non-displaced workers compare? We see in column 6 of Table 8, each standard deviation increase in last job skill is predicted to change ΔSKL by -0.00 (0.00), -0.05 (0.01), and -0.10 (0.01) at low, medium and high angular separation. Each standard deviation increase in angular separation is predicted to change ΔSKL by 0.08 (0.01), 0.03 (0.01), and -0.02 (0.01). Two of the estimated effects for non-displaced workers are thus quite muted compared with those of non-displaced workers: the effects of last job rank at high angular separation, and the effects of angular separation at high last job rank. However, the overall magnitude of the effects continues to be similar for both groups of workers, and reinforces once again the notion that similar – but not, of course, identical – economic processes are work.

5.4 Threats to Identification

The identification of causal effects relies on the assumption that the instruments are valid, meaning that they do not belong in the second stage regressions. There are two endogenous variables in Equation 29 and two excluded regressors, and so we cannot conduct the usual tests for over-identification. Instead, we carry out a series of informal tests, the results of which suggest that our exclusion restrictions are valid.

Let $\mathbf{A}$ denote the set of endogenous regressors involving angular separation. Recall that our instrumental variables strategy involves a first stage regression of $\mathbf{A}$ on $\mathbf{X}$ and $\tilde{\mathbf{Z}}^{oth}$, where the $\mathbf{X}$ denotes the exogenous regressors in the second stage regressions, and the latter is the vector of excluded instruments based on means of the other group of workers, that is, non-displaced workers when we are analyzing displaced workers, and displaced workers when we are analyzing non-displaced workers.

Consider now the alternative set of instruments $\tilde{\mathbf{Z}}^{own}$, based on occupation-level means for the own-group, but excluding the individuals own values of $\mathbf{A}$ from each individual's observation. While somewhat less plausible, certainly one would expect $\tilde{\mathbf{Z}}^{own}$ to be just as, if not more powerful than $\tilde{\mathbf{Z}}^{oth}$. Moreover, by using $\tilde{\mathbf{Z}}^{own}$ as the excluded instruments, we now have the option of including $\tilde{\mathbf{Z}}^{oth}$ in the second stage regressions and testing for their significance with a simple chi-square test.

Summarizing these results, which we suppress to reduce clutter, there is no evidence that the exclusion restrictions are violated. Nor is there evidence that the own-instrument set $\tilde{\mathbf{Z}}^{own}$ belongs in the second stage when we use $\tilde{\mathbf{Z}}^{oth}$ as excluded instruments.

6 Wages

We now estimate how the effects of lost job rank, skill and change in skill composition translate into wages. Most work on the effects of displacement on earnings concentrate on the mean, and little attention has been devoted to characterizing the overall distribution of earnings changes among displaced worker. However, this situation is changing. For example, Farber (2017) finds that a substantial fraction of workers experience earnings increases after displacement, even after accounting for measurement error. Another exception is Pung (2017), who shows that the distribution of earnings losses is negatively skewed, with a mean more than twice the median, and that a substantial fraction of displaced workers actually experience earnings gains.

6.1 Overview of Wage Changes

Our findings thus far indicate that the change in rank between the lost and current job is negatively related to lost job rank. If earnings are positively related to job rank, this result suggests that we should find a negative relationship between the magnitude of earnings losses and lost job rank. Summary evidence on this point, seen in Table 9, is broadly supportive of this point. Looking at columns 1-2, workers displaced from jobs in the first three deciles experience earnings reductions of between 0.010 and 0.039 log points, compared with 0.041-0.069 log points for workers displaced from jobs in the 4th through 6th deciles, rising to 0.078-0.098 log points for deciles 7 through 9, and 0.12 log points for the 10th decile. The broad story also holds for workers displaced due to plant closure, with losses of 0.00 to 0.054 log points for workers in deciles 1 through 6, and on the order of 0.10 log points for workers in deciles 7 through 10. The figures in columns 4-5 that condition on switching occupation also indicate that earnings losses tend to be higher for workers displaced from more highly ranked jobs.

Broadly speaking, the summary evidence in Table 9 is consistent with the Farber (2017). He finds that the probability of earnings increases is particularly high for younger workers and those with less tenure on the lost job, and wage losses are concentrated among those with the very highest – 20 years or more – of job tenure.[29] Such workers are precisely those who should be employed in lower-ranked jobs.

[29]The fraction with positive earnings changes declines from over 50% for job losers 20-24 years old to about 10% of job losers 55-64 years old, and from 43% of job losers in their first year on the lost job to about 4% of job losers with at least 20 years of tenure on the lost job (S266). Why did these workers not leave their lost job voluntarily? Farber (2017) points out a number of reasons. First, the new job may not be better than the old job despite offering higher earnings. In addition, job search is costly. Workers, too, may be risk-averse and hence unwilling to change jobs voluntarily.

The summary evidence is not supportive across the board. For example, the magnitude of earnings "losses" actually declines between deciles 1 and 3 for displaced workers as a whole, and between deciles 1 and 5 for those displaced due to a plant closure. However, our heuristic model points out that the effects of rank interact with changes in skill composition, not accounted for in these summary statistics. Nor do these summary figures take into account for the roles of job tenure or age (Farber, 2017). Our empirical analysis of wages will reveal how accounting for these factors within a simple regression model affects matters.

6.2 Regression Analysis of Wages

We assume that lost job rank, lost job skill, and changes in skill composition affect earnings only through their effects on ΔRNK_{ijk} and ΔSKL_{ijk}.[30] We specify the change in log earnings for individual i between the lost job j and current job k as

$$\Delta W_{ijk} = \beta_0^W + \beta_R^W \Delta RNK_{ijk} + \beta_S^W \Delta SKL_{ijk} + \beta_X^W X_{ij} + \epsilon_{ijk}, \tag{30}$$

where ΔW is the change in log earnings.[31] Because ΔRNK_{ijk} and ΔSKL_{ijk} are endogenous, the system contains three equations, which we estimate using three stage least squares. The standard errors continue to be clustered on 1990 IPUMS occupation of the lost job, calculated via a bootstrap using 150 replications.

6.2.1 Effects of Changes in Rank and Skill on Wages

Selected coefficients for Equation 30 are contained in Table 10. The estimated coefficients on the various controls are unremarkable. Turning to the coefficients of main interest, the estimated coefficients on ΔRNK_{ijk} and ΔSKL_{ijk} are positive and statistically significant. Each 10 percentile point increase in job rank is estimated to raise wage growth by 0.012 log points for displaced workers as a whole, by 0.016 log points for workers displaced due to a plant closing, and a smaller, but still significant 0.004 log points for non-displaced workers. The estimated effects of an 0.10 increase in ΔSKL_{ijk} on wages are 0.021, 0.026, and 0.020 log points, respectively.

6.2.2 Effects of Lost/Last Job Rank and Skill and Angular Separation on Wages

We now evaluate the effects on earnings of a standard deviation increase in lost job rank, lost job skill, and angular separation on earnings.[32] Before turning to these calculations, we observe that estimates of the effects of lost job rank or skill and angular separation from the rank and skill

[30] We experimented with a less restrictive specification in which $ANGL_{ijk}$ enters independently as well as via ΔRNK_{ijk}. The resulting estimates are noisy and uninformative, an unsurprising result in light of the fact that both the direct and indirect effects of the variables in question are being instrumented.

[31] The mapping from rank to earnings is subtle. Lazear (2009) adopts a Nash bargaining framework in which workers attached themselves to a firm at the start of their career. Investments in skills are affected by the fact that later periods are characterized by bilateral monopoly (917). The equilibrium paths of investment and earnings account for the distribution of workers' values to outside firms, which generally place weights on workers' acquired skills differently than the initial firm.

[32] The effect of a standard deviation increase in $LRNK_{ij}$, σ_R, on earnings is equal to

$$\sigma_R \times \{\hat{\beta}_R^W(\hat{\beta}_R^R + \hat{\beta}_{RA}^R ANGL_{ijk}) + \hat{\beta}_S^W(\hat{\beta}_R^S + \hat{\beta}_{SA}^S ANGL_{ijk})\}, \tag{31}$$

where subscripts on the regressors have been suppressed to reduce clutter. The effect of a standard deviation increase in lost job skill is computed similarly. The effect of a standard deviation increase in $ANGL$, σ_A, on earnings is equal regressions using the wage sample are similar to those using the rank sample. The similarity for displaced workers is unsurprising, because the earnings sample is a subset of the rank sample. This is not, however, the case for non-displaced workers because analysis of the earnings sample uses data solely from rotations 4 and 8, one year apart, whereas the analysis in the rank sample uses data from all rotations except 1 and 5, just one month apart.

The effect on earnings, in log points, of a standard deviation increase in lost job rank is:

- -0.005 (s.e.=0.002) at low angular separation
- -0.017 (s.e.=0.005) at mean angular separation
- -0.029 (s.e.=0.009) at high angular separation.

Interestingly, the estimated effects of a standard deviation increase in lost job skill are very close in magnitude. The magnitudes for workers displaced due to a plant closing are somewhat larger, -0.006 (0.004), -0.024 (0.006), and -0.041 (0.010) for lost job rank. The effects of lost job rank for non-displaced workers are markedly smaller, at -0.001 (0.001), -0.005 (0.002), and -0.009 (0.004). The estimated effects of a standard deviation increase in job skill are quite similar in magnitude as for rank for displaced workers, but somewhat larger for non-displaced workers: -0.005 (.001), -0.016 (0.002), and -0.027 (0.003).

Angular separation affects earnings through both ΔRNK_{ij} and ΔSKL_{ij}, We therefore evaluate the sum of these effects, evaluated at low, medium, and high values of *both* lost job rank and skill. The results for displaced workers as a whole are:

- +0.026 (s.e.=0.007) at low lost job rank and skill
- -0.000 (s.e.=0.002) at mean lost job rank and skill
- -0.027 (s.e.=0.007) at high lost job rank skill.

Again, the magnitudes for workers displaced due to a plant closure are larger, at 0.037 (0.009), 0.001 (0.004), and -0.036 (0.007), while those for non-displaced workers are smaller, at 0.019 (0.004), 0.004 (0.001), and -0.011 (0.003).

7 Do High-Rank Workers Avoid Skill Changes?

The estimates indicate that changes in skill composition are costly for workers who lose high-rank jobs, high-skill jobs. The question naturally arises whether there is any evidence that they are able to avoid such changes.

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to

$$\sigma_A \times \{\hat{\beta}_R^W(\hat{\beta}_A^R + \hat{\beta}_{RA}^R LRNK_{ij}) + \hat{\beta}_S^W(\hat{\beta}_A^S + \hat{\beta}_{SA}^S LSKL_{ij})\}, \tag{32}$$

where $\hat{\beta}_A^W$ and $\hat{\beta}_S^W$ are the estimated coefficients on ΔRNK_{ijk} and ΔSKL_{ijk} from Equation 30, $\hat{\beta}_A^R$ and $\hat{\beta}_A^S$ are the estimated coefficients on $ANGL_{ijk}$ in the rank and skill equations, and $\hat{\beta}_{RA}^R$ ($\hat{\beta}_{SA}^S$) is the estimated coefficient on the interaction between lost job rank (skill) and angular separation.

7.1 Occupation Switches

One way to avoid changes in the skill composition of the job is to find a new job in the same occupation as the old. We estimate linear probability models for changing occupation using the rank sample, specified as

$$\Delta OCC_{ijk} = \alpha_0^O + \alpha_R^O LRNK_{ij} + \alpha_S^O LSKL_{ij} + \alpha_X^O X_{ij} + \nu_{ij}^O, \tag{33}$$

where ΔOCC_{ij} equals unity if the occupation of individual i on the lost job j differs from that of the new job k and equals zero otherwise, and the other variables are as before. The results are contained in columns 1-3 of Table 13. Again, the standard errors are clustered on 3-digit IPUMS (1990) occupation.

Before turning to the estimated effects of lost job rank and skill, we point out that all of the tenure indicators but one (11-20) are negative, indicating that the chances of switching occupation are higher for this group and the omitted group (less than 1 year) than the other, included groups. Younger workers are more likely to switch occupation relative to the omitted group (35-44), while dropouts are less likely to switch occupation than the omitted category (high school graduates).

The estimated coefficients on lost job rank, seen in the first row, are about the same for displaced workers as a whole and those displaced due to plant closure, and actually positive at 0.002 (0.001). Thus, workers displaced from highly-ranked jobs do not avoid occupation switches more often than workers displaced from low-ranked jobs. Why this is the case is beyond the scope of this paper, but could have something to do with the choice set. For example, Sessa (2018) finds that the transition of workers out of unemployment is faster, the faster the rate of growth of the worker's old industry.[33]

Interestingly, the estimated coefficients on lost job skill are negative and statistically significant, equal to -0.298 (0.060) and -0.270 (0.056). Again, we leave explanation for this result for future research, but it could have to do with the nature of high-skill jobs, which could be in higher demand and be more evenly distributed across industries.

The results for non-displaced workers, contained in column 3, are markedly different than those for displaced workers. For example, the estimated coefficient on lost job rank is negative, but is economically as well as statistically indistinguishable from zero. Nearly every other coefficient is an order of magnitude smaller than for displaced workers, and the regression explains about one-tenth of the variation in the data, with an R-Square of 0.003 versus R-Squares of 0.033 and 0.037. This result should not be surprising. Few non-displaced workers change occupation from one month to another, much less employer.

7.2 Angular Separation

We next consider whether workers who lose high-rank jobs are more likely to find jobs more similar in skill composition to their lost job than workers who lose low rank jobs. There is little sense on including workers who do not switch occupations in this analysis, for whom $ANGL_{ijk} = 0$, since we have just established that high rank workers are no more likely to find jobs in their original

[33] Speculating, a worker displaced from a grinding and polishing job due to a plant closure may have trouble finding a new grinding and polishing job because the plants that have not yet closed are under similar economic pressures as the one that closed, and are not hiring.

occupation than low-rank workers.[34] We therefore estimate the regression given by

$$ANGL_{ijk} = \alpha_0^A + \alpha_R^A LRNK_{ij} + \alpha_S^A LSKL_{ij} + \alpha_X^A X_{ij} + \nu_{ij}^A \quad \text{if } \Delta OCC_{ijk} = 1, \tag{34}$$

and implement Heckman's two-step procedure to control for selection.

The results are seen in columns 4-6 of Table 13. We identify the sample selection equation by including the mean propensity to leave the lost job occupation of *non-displaced* workers in the sample of displaced workers, and the mean propensity of displaced workers in the sample of non-displaced workers. The estimated coefficients on age suggest that younger workers make larger career trajectory changes than do older workers, while those on education suggest that both the least educated and the most educated make larger changes than high school graduates.

The estimated coefficient on lost job rank is -0.121 (0.040) for displaced workers as a whole (column 4), and equal to -0.131 (0.056) for workers displaced due to a plant closure (column 5). Both results are consistent with the notion that conditional on switching occupation, higher-rank workers experience smaller changes in career trajectory. The estimated coefficients on lost job skill are of opposite algebraic signs and imprecisely estimated.

Why are the results for $ANGL$ more supportive of our hypothesis than for occupation switching? Above, we speculated that economic forces, including the costs of search, could make it prohibitively costly to find jobs in one's old occupation. In fact, the relationship between lost job rank and occupational change was virtually zero even for non-displaced workers, which raises the possibility that the difficulty of finding work in one's old occupation is not limited to displaced workers. In fact, across 754 occupations, the pairwise correlation between the proportion switching occupations among displaced workers and among non-displaced workers who switch employers is 0.4084, dropping to a still high 0.3662 for workers displaced due to a plant closure. Weighted by displaced worker cell size, the correlations are even higher: 0.73 and 0.67. Whatever it is that is preventing displaced workers from finding new jobs in their old occupation, it would appear that similar forces are at work for non-displaced workers who change employer.

8 Conclusion

This paper makes a number of contributions to the literature on displaced workers. First, we motivate our empirical analysis with a heuristic model of job transition within a task-specific human capital framework (Gibbons and Waldman, 2004; Lazear, 2009) that yields a rich set of predictions. In particular, the model shows that because new career trajectories employ skills in proportions different than the one on the lost job, a worker's potential in those new careers is limited by her relatively scarce skill. The model shows that these limitations are more severe, (1) the higher the rank of the lost job and (2) the greater the change in skill composition, with a strong negative interaction between the two. Second, from our heuristic model occupational rank of the job emerges as a key outcome, read, dependent variable rather than solely as a regressor. Third, out of our heuristic model, we show that angular separation (Gathmann and Schönberg, 2010) between skill vectors on the lost and current job emerges as a natural and pure measure of skill composition change, as opposed to Euclidean distance measures that combine the effects of composition and rank. Fourth, we address the problem of endogeneity of angular separation by exploiting the

[34]Notice that Equation 34 excludes the mean values of $ANGL_{ijk}$ of non-displaced workers, which were included in the first stage Equation 29. The difference in specification reflects the difference in purpose, namely, hypothesis testing versus prediction.

similarity of mean values of angular separation at the occupation level between displaced and non-displaced workers, using the latter as an instrument for individual-level values of the former. We show, too, that the effects of lost job rank and changes in skill composition operate in a similar fashion for non-displaced workers. This does not mean, of course, that there is no difference between being displaced and not. However, it does suggest that the economic forces in operation are not dissimilar.

Two additional findings are of interest. First, the effects of changes in skill composition on job rank and earnings are positive for workers who lose low-rank jobs. The model can accommodates this by suggesting that low-rank workers may need to make larger changes in career trajectory in order to progress up the job ladder. Finally, we find evidence consistent with the notion that workers displaced from high-rank jobs try to avoid costly changes in skill composition, conditional on changing occupation, for which group such changes are particularly costly.

There are a number of areas on which further research is necessary. For example, we found that there was a high correlation between mean values of angular separation by occupation for displaced and non-displaced workers. Why those mean values differ across occupations was not addressed, however. Second, workers who lose high-rank jobs have more to lose by changing occupations. However, we find that they are no less (or more) likely to switch occupation than workers who lose low-rank jobs. While one can speculate as to why this is the case, further research seems necessary on this point.

References

David Autor and David Dorn. Explaining job polarization: Routine-biased technological change and offshoring. *The American Economic Review*, 104(8):2509–2526, 2014. doi: doi:10.1257/aer.104.8.2509. URL http://www.ingentaconnect.com/content/aea/aer/2014/00000104/00000008/art00009.

George Baker, Michael Gibbs, and Bengt Holmstrom. The wage policy of a firm*. *The Quarterly Journal of Economics*, 109(4):921–955, 1994. doi: 10.2307/2118352. URL + http://dx.doi.org/10.2307/2118352.

Henry S. Farber. Employment, hours, and earnings consequences of job loss: Us evidence from the displaced workers survey. *Journal of Labor Economics*, 35(S1):S235–S272, 2017. doi: 10.1086/692353. URL https://doi.org/10.1086/692353.

Eliza Forsythe. Occupational job ladders and the efficient reallocation of displaced workers. Working Paper, April 2017.

Anders Frederiksen and Takao Kato. Human capital and career success: Evidence from linked employer-employee data. *The Economic Journal*, 0(0), 2017. doi: 10.1111/ecoj.12504. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/ecoj.12504.

Mallika Garg. *Unobserved Heterogeneity and Self-Selection: Essays in Labor Economics and International Trade*. PhD thesis, Clemson University, 2016.

Christina Gathmann and Uta Schönberg. How general is human capital? a task-based approach. *Journal of Labor Economics*, 28(1):1–49, 2010. ISSN 0734306X, 15375307. URL http://www.jstor.org/stable/10.1086/649786.

Robert Gibbons and Michael Waldman. Task-specific human capital. *American Economic Review*, 94(2):203–207, May 2004. doi: 10.1257/0002828041301579. URL http://www.aeaweb.org/articles?id=10.1257/0002828041301579.

Fane Groes, Philipp Kircher, and Iourii Manovskii. The U-Shapes of Occupational Mobility. *The Review of Economic Studies*, 82(2):659–692, 10 2014. ISSN 0034-6527. doi: 10.1093/restud/rdu037. URL https://dx.doi.org/10.1093/restud/rdu037.

John C. Haltiwanger, Henry R. Hyatt, Lisa B. Kahn, and Erika McEntarfer. Cyclical job ladders by firm size and firm wage. *American Economic Journal: Macroeconomics*, 10(2):52–85, April 2018. doi: 10.1257/mac.20150245. URL http://www.aeaweb.org/articles?id=10.1257/mac.20150245.

Michael Handel. Methodological issues related to the occupational requirements survey. 2015. URL https://www.bls.gov/ncs/ors/handel-methodological-issues-data-collection-full-report-feb15.pdf.

Illoong Kwon and Eva M. Meyersson Milgrom. The significance of firm and occupation specific human capital for hiring and promotions. *Labour Economics*, 31:162 – 173, 2014. ISSN 0927-5371. doi: https://doi.org/10.1016/j.labeco.2014.07.003. URL http://www.sciencedirect.com/science/article/pii/S0927537114000864.

Edward Lazear. The job as a concept. In William J Bruns, editor, *Performance Measurement, Evaluation, and Incentives*, chapter 7, pages 183–215. Harvard Business School Press, Boston, MA, 1992.

Edward P. Lazear. The peter principle: A theory of decline. *Journal of Political Economy*, 112(S1):S141–S163, 2004a. ISSN 00223808, 1537534X. URL `http://www.jstor.org/stable/10.1086/379943`.

Edward P. Lazear. The peter principle: A theory of decline. *Journal of Political Economy*, 112 (S1):S141–S163, 2004b. doi: 10.1086/379943. URL `https://doi.org/10.1086/379943`.

Edward P. Lazear. Firm-specific human capital: A skill-weights approach. *Journal of Political Economy*, 117(5):914–940, 2009. doi: 10.1086/648671. URL `https://doi.org/10.1086/648671`.

Edward P. Lazear and Sherwin Rosen. Rank-order tournaments as optimum labor contracts. *Journal of Political Economy*, 89(5):841–864, 1981. ISSN 00223808, 1537534X. URL `http://www.jstor.org/stable/1830810`.

Kevin M. Murphy. *Specialization and Human Capital*. PhD thesis, University of Chicago, August 1986.

Maxim Poletaev and Chris Robinson. Human capital specificity: Evidence from the dictionary of occupational titles and displaced worker surveys, 1984–2000. *Journal of Labor Economics*, 26(3):387–420, 2008. ISSN 0734306X, 15375307. URL `http://www.jstor.org/stable/10.1086/588180`.

Canice Prendergast. The role of promotion in inducing specific human capital acquisition. *The Quarterly Journal of Economics*, 108(2):523–534, 1993. ISSN 00335533, 15314650. URL `http://www.jstor.org/stable/2118343`.

Mallika Pung. Heterogeneity in earnings losses of displaced workers: Evidence from the united states. September 2017.

Christopher Robinson. Occupational mobility, occupation distance, and specific human capital. *Journal of Human Resources*, 53(2), Spring 2018.

Steven Ruggles Sarah Flood, Miriam King and J. Robert Warren. *Integrated Public Use Microdata Series, Current Population Survey: Version 5.0. [dataset]*. University of Minnesota, Minneapolis, Minnesota, 2017. URL `https://doi.org/10.18128/D030.V5.0`.

David Scoones and Dan Bernhardt. Promotion, turnover, and discretionary human capital acquisition. *Journal of Labor Economics*, 16(1):122–141, 1998. doi: 10.1086/209884. URL `https://doi.org/10.1086/209884`.

Richard Sessa. *Three Essays on Sectoral Change and Unemployment*. PhD thesis, Clemson University, May 2018.

Dixie Sommers, Ken Baker, Sue Berryman, and Manfred Emmrich. The new dot: A database of occupational titles for the twenty-first century. Technical report, May 1993.

Paul Sullivan. Empirical evidence on occupation and industry specific human capital. *Labour Economics*, 17(3):567 – 580, 2010. ISSN 0927-5371. doi: https://doi.org/10.1016/j.labeco.2009.11.003. URL http://www.sciencedirect.com/science/article/pii/S0927537109001286.

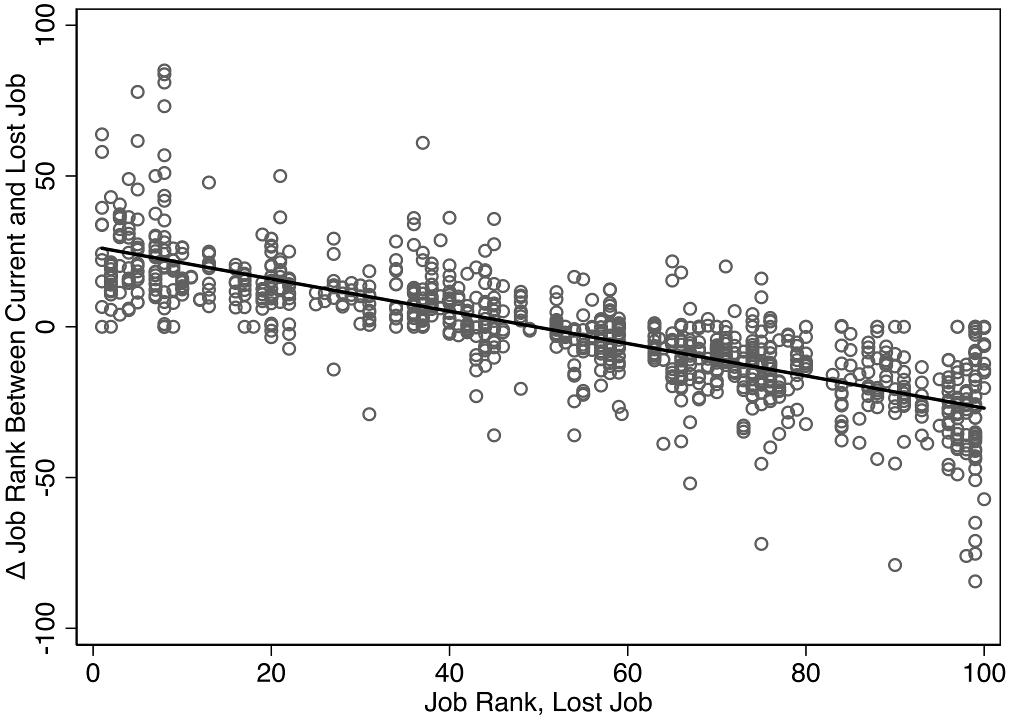

Figure 1: Change in Job Rank Versus Lost Job Rank, Displaced Workers

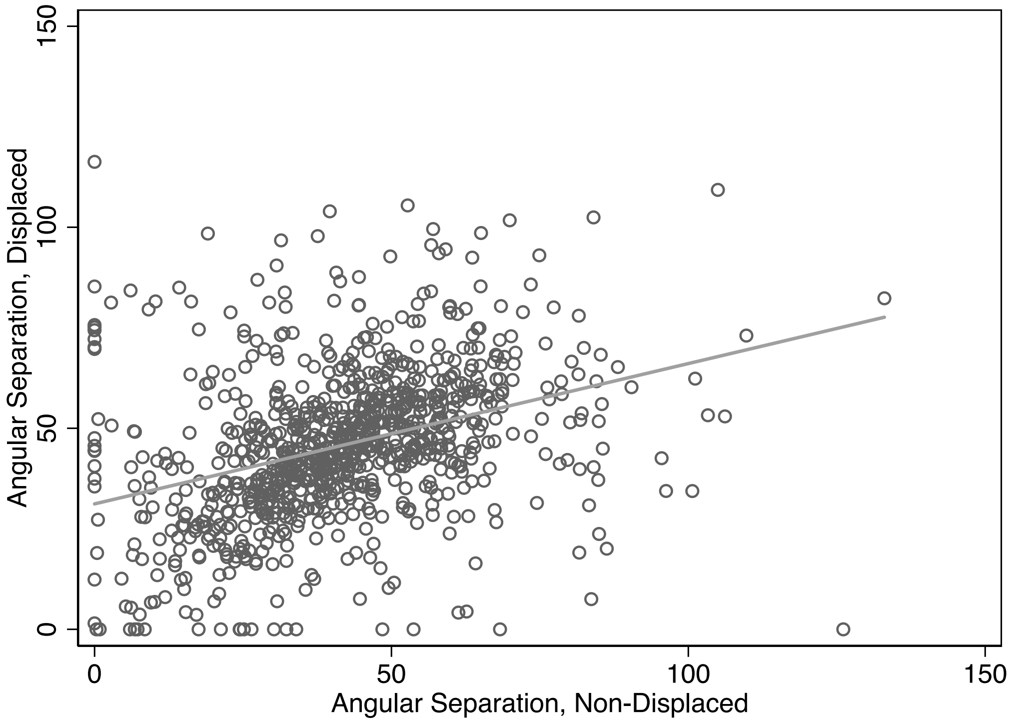

Figure 2: Angular Separation, Displaced versus Non-Displaced

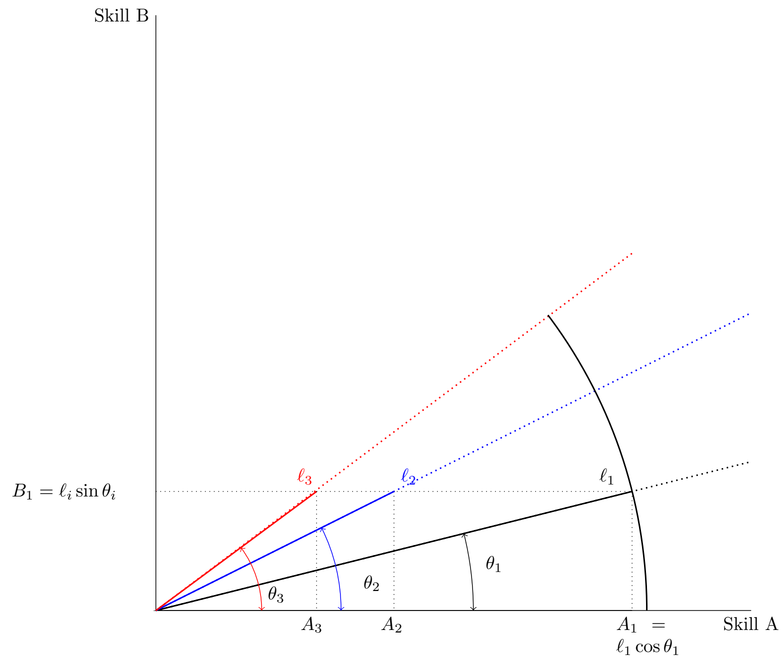

Figure 3: Theoretical Model: Basic Mechanism, Angular Separation

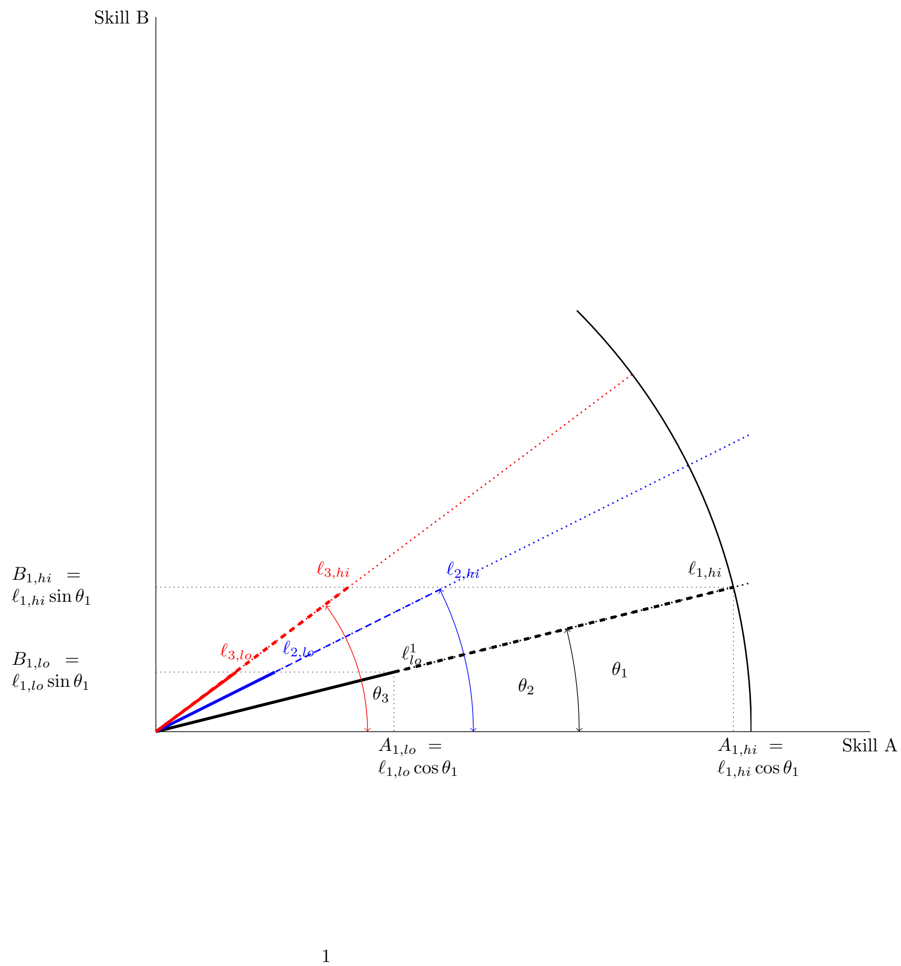

Figure 4: Theoretical Model: Basic Mechanism, Lost Job Rank

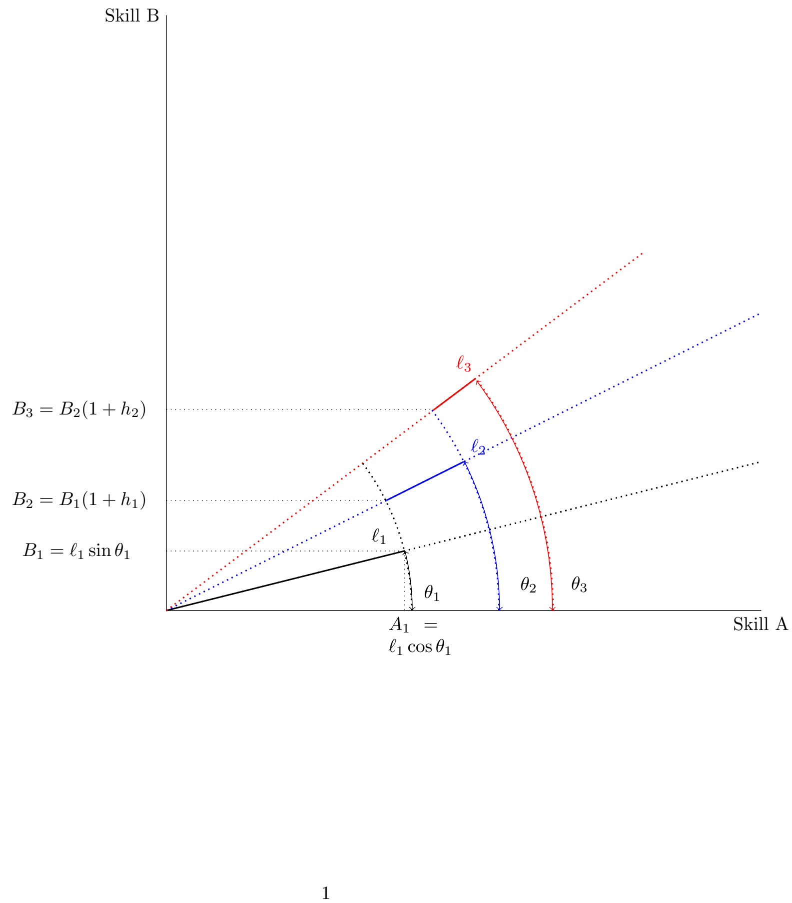

Figure 5: Theoretical Model: Differences in Potential for Advancement Across Career Trajectories

Table 1: 20 Highest and Lowest-Rank Occupations, with Changes for Occupation Switchers

	Displaced			Not Displaced	
Occupation	*RNK*	Displ	Plant Cl	All	Δ Emp
Chief executives and public administrators	100	-27	-27	-31	-24
Pharmacists	99	-29	-6	-41	-49
Managers and specialists in marketing and kindred	98	-34	-38	-29	-30
Auto body repairers	98	-33	-41	-28	-24
Grinding, abrading, buffing, and polishing workers	98	-49	-51	-38	-36
Financial services sales occupations	97	-33	-42	-33	-31
Butchers and meat cutters	97	-39	-38	-41	-43
Production checkers and inspectors	97	-37	-37	-30	-35
Licensed practical nurses	96	-35	-55	-38	-36
Supervisors of mechanics and repairers	96	-27	-29	-24	-26
Supervisors and proprietors of sales jobs	93	-34	-36	-30	-31
Aircraft mechanics	93	-32	-27	-25	-24
Managers and administrators, n.e.c.	91	-23	-24	-21	-20
Buyers, wholesale and retail trade	90	-24	-32	-28	-22
Computer systems analysts and computer scientists	89	-17	-18	-18	-16
Management analysts	89	-15	-17	-22	-18
Production supervisors or foremen	88	-28	-30	-22	-18
Lawyers	88	-31	-5	-24	-40
Electrical engineer	87	-17	-12	-15	-13
Automobile mechanics	87	-21	-17	-29	-28
Carpenters	19	27	29	29	28
Architects	19	31	2	43	47
Construction laborers	17	26	35	30	28
Helpers, surveyors	17	26	26	29	28
Misc food prep workers	17	19	19	21	18
Construction laborers	17	26	35	30	28
Masons, tilers, and carpet installers	16	31	43	25	18
Truck, delivery, and tractor drivers	13	39	37	38	34
Gardeners and groundskeepers	11	34	38	36	33
Housekeepers, maids, butlers, and kindred	10	32	31	34	31
Kindergarten and earlier school teachers	10	21	28	19	14
Guards, watchmen, doorkeepers	9	51	51	47	47
Farm workers	7	37	35	36	37
Roofers and slaters	7	44	30	40	35
Writers and authors	7	46	26	49	56
Primary school teachers	5	18	12	37	33
Door-to-door sales, street sales, and news vendors	3	47	38	59	60
Teachers , n.e.c.	3	55	56	47	43
Taxi cab drivers and chauffeurs	2	27	28	41	48
Child care workers	2	28	37	40	47

Figures for occupation switchers in the rank change samples. *RNK* is rank of the lost/last job,

Table 2: Rank Changes by Lost Job Rank, Top and Bottom 20

		Displaced		Not Displaced	
Occupation	Job Rank	All	Plant Cl	All	Δ Emp
Teachers , n.e.c.	3	55	56	47	43
Guards, watchmen, doorkeepers	9	51	51	47	47
Door-to-door sales, street sales, and news vendors	3	47	38	59	60
Writers and authors	7	46	26	49	56
Roofers and slaters	7	44	30	40	35
Editors and reporters	21	39	50	32	25
Truck, delivery, and tractor drivers	13	39	37	38	34
Farm workers	7	37	35	36	37
Miners	37	35	45	22	19
Gardeners and groundskeepers	11	34	38	36	33
Interviewers, enumerators, and surveyors	21	33	32	33	32
Housekeepers, maids, butlers, and kindred	10	32	31	34	31
Architects	19	31	2	43	47
Masons, tilers, and carpet installers	16	31	43	25	18
Bookkeepers and accounting and auditing clerks	27	30	28	27	26
Child care workers	2	28	37	40	47
Cashiers	22	28	28	32	26
Carpenters	19	27	29	29	28
Taxi cab drivers and chauffeurs	2	27	28	41	48
Excavating and loading machine operators	22	27	25	23	6
Crane, derrick, winch, and hoist operators	54	-26	-20	-3	5
Supervisors of motor vehicle transportation	84	-26	-8	-19	-16
Chief executives and public administrators	100	-27	-27	-31	-24
Supervisors of mechanics and repairers	96	-27	-29	-24	-26
Production supervisors or foremen	88	-28	-30	-22	-18
Pharmacists	99	-29	-6	-41	-49
Printing machine operators, n.e.c.	86	-30	-31	-25	-30
Dispatchers	84	-31	-40	-30	-28
Painting machine operators	84	-31	-27	-21	-25
Lawyers	88	-31	-5	-24	-40
Bill and account collectors	75	-32	-38	-18	-12
Aircraft mechanics	93	-32	-27	-25	-24
Auto body repairers	98	-33	-41	-28	-24
Financial services sales occupations	97	-33	-42	-33	-31
Managers and specialists in marketing and kindred	98	-34	-38	-29	-30
Supervisors and proprietors of sales jobs	93	-34	-36	-30	-31
Licensed practical nurses	96	-35	-55	-38	-36
Production checkers and inspectors	97	-37	-37	-30	-35
Butchers and meat cutters	97	-39	-38	-41	-43
Grinding, abrading, buffing, and polishing workers	98	-49	-51	-38	-36

The figures in the table are ordered by the means for displaced workers as a whole. Data for non-displaced workers based on rotations 2-4 and 6-8.

Table 3: Angular Separation Among Occupation Switchers, Top and Bottom 20

Occupation	Displaced		Not Displaced	
	All	Closure	All	Δ Emp
	(1)	(2)	(3)	(4)
Computer and peripheral equipment operators	100	102	101	102
Production supervisors or foremen	97	97	96	96
Guards, watchmen, doorkeepers	96	92	86	84
Kindergarten and earlier school teachers	93	109	80	79
Payroll and timekeeping clerks	91	91	73	75
Bookkeepers and accounting and auditing clerks	90	95	83	81
Teachers , n.e.c.	89	98	84	82
Billing clerks and related financial records processing	89	85	71	65
Pharmacists	88	89	75	60
Bank tellers	86	90	90	86
Dental laboratory and medical appliance technicians	86	89	81	73
Health technologists and technicians, n.e.c.	86	87	76	77
Secretaries	85	86	85	88
Cashiers	85	78	89	84
Miners	85	84	66	67
Architects	84	139	60	60
Typists	84	65	72	68
Butchers and meat cutters	84	76	65	71
Data entry keyers	83	96	77	74
Supervisors of mechanics and repairers	83	84	72	74
Crane, derrick, winch, and hoist operators	50	98	70	75
Wood lathe, routing, and planing machine operators	50	43	54	63
Operations and systems researchers and analysts	50	55	52	55
Drillers of oil wells	49	33	55	56
Molders, and casting machine operators	49	62	56	56
Management analysts	48	46	53	49
Buyers, wholesale and retail trade	48	61	56	40
Electrical engineer	47	43	51	47
Drywall installers	47	41	52	47
Heavy equipment and farm equipment mechanics	46	42	57	62
Industrial engineers	45	43	55	50
Computer software developers	45	47	47	43
Human resources and labor relations managers	44	57	37	40
Economists, market researchers, and survey researchers	43	36	44	43
Financial services sales occupations	43	48	47	44
Writers and authors	41	40	58	53
Financial managers	41	41	44	40
Not-elsewhere-classified engineers	40	41	46	45
Managers of service organizations, n.e.c.	36	43	44	37
Chief executives and public administrators	32	33	41	29

These data show mean levels of Angular Separation. Data on the comparison group includes only those workers for whom a change in employer can be identified, that is, in rotations 2-4 and 6-8.

Table 4: Changes in Job Rank by Lost Job Rank Decile

	All Job Changes				Occupation Changes			
	Displaced		Not Displaced		Displaced		Not Displaced	
Decile	All (1)	Closure (2)	All (3)	Δ Emp (4)	All (5)	Closure (6)	All (7)	Δ Emp (8)
1	27	26	1	21	42	40	41	39
2	16	16	1	13	31	33	32	28
3	17	17	1	13	25	26	25	22
4	10	9	1	9	17	15	20	17
5	5	6	0	4	7	9	10	7
6	-1	-0	0	-0	-1	-0	1	-0
7	-7	-8	-0	-4	-11	-11	-7	-7
8	-8	-7	-0	-7	-11	-10	-12	-12
9	-13	-14	-1	-9	-22	-23	-21	-19
10	-22	-23	-1	-15	-31	-33	-28	-28

These data show mean changes in job rank. Data on the comparison group includes only those workers for whom a change in employer can be identified, that is, in rotations 2-4 and 6-8.

Table 5: Angular Separation by Lost Job Rank Decile

	All Job Changes				Occupation Changes			
	Displaced		Not Displaced		Displaced		Not Displaced	
Decile	All (1)	Closure (2)	All (3)	Δ Emp (4)	All (5)	Closure (6)	All (7)	Δ Emp (8)
1	49	52	3	39	76	81	74	73
2	37	36	2	31	72	74	71	70
3	51	50	3	45	75	75	74	73
4	43	41	3	37	68	71	68	68
5	48	47	3	39	73	74	75	73
6	47	47	3	41	65	65	65	65
7	46	47	2	36	70	67	66	64
8	41	39	2	32	61	60	59	58
9	38	40	2	26	63	66	61	58
10	41	44	2	30	59	63	55	55

These data show mean levels of Angular Separation. Data on the comparison group includes only those workers for whom a change in employer can be identified, that is, in rotations 2-4 and 6-8.

Table 6: Summary Statistics

	Rank Sample			Earnings Sample		
	Displ	Plantcl	Not Displ	Displ	Plantcl	Not Displ
Lost/Last Job Rank	58.221	59.537	58.718	58.419	59.754	59.206
	(26.343)	(26.109)	(27.521)	(26.386)	(26.100)	(27.285)
Lost/Last Job Skill	0.020	0.010	0.044	0.023	0.012	0.044
	(0.199)	(0.198)	(0.201)	(0.199)	(0.198)	(0.200)
$\Delta Rank$	-1.421	-2.170	0.033	-1.490	-2.053	0.040
	(26.965)	(26.532)	(16.461)	(27.102)	(26.481)	(21.569)
$\Delta Skill$	-0.008	-0.012	-0.000	-0.009	-0.013	0.000
	(0.168)	(0.169)	(0.109)	(0.168)	(0.169)	(0.133)
Angular Distance	43.403	43.083	15.507	43.719	43.270	27.750
	(41.840)	(42.288)	(34.029)	(41.886)	(42.283)	(37.663)
× Occ Rank	25.049	25.573	8.834	25.350	25.766	16.052
	(28.589)	(29.461)	(21.727)	(28.797)	(29.584)	(24.694)
× Occ Skill	-0.269	-0.411	0.313	-0.201	-0.311	0.458
	(11.226)	(11.107)	(7.265)	(11.251)	(11.053)	(8.766)
Angular Distance, Occ Changers	66.047	66.919	71.643	66.040	66.871	59.043
	(34.180)	(34.386)	(36.443)	(34.293)	(34.419)	(34.212)
× Occ Rank	38.117	39.722	40.811	0.383	0.398	0.342
	(27.306)	(28.038)	(29.595)	(0.275)	(0.282)	(0.261)
× Occ Skill	-0.409	-0.639	1.448	-0.304	-0.481	0.975
	(13.846)	(13.838)	(15.563)	(13.827)	(13.738)	(12.767)
Tenure 1-3 Years	0.317	0.291		0.317	0.291	
	(0.465)	(0.454)		(0.465)	(0.454)	
Tenure 3-10 Years	0.352	0.380		0.360	0.387	
	(0.478)	(0.485)		(0.480)	(0.487)	
Tenure 11-20 Years	0.090	0.114		0.093	0.119	
	(0.287)	(0.318)		(0.291)	(0.324)	
Tenure 20+ Years	0.060	0.077		0.042	0.059	
	(0.237)	(0.267)		(0.202)	(0.235)	
Displaced 1 Year Ago	0.342	0.314		0.344	0.316	
	(0.474)	(0.464)		(0.475)	(0.465)	
Displaced 3 Years Ago	0.308	0.349		0.311	0.347	
	(0.462)	(0.477)		(0.463)	(0.476)	
Age 20-24	0.083	0.076	0.046	0.083	0.077	0.036
	(0.277)	(0.266)	(0.210)	(0.276)	(0.266)	(0.186)
Age 25-34	0.295	0.289	0.221	0.299	0.289	0.215
	(0.456)	(0.454)	(0.415)	(0.458)	(0.453)	(0.411)
Age 45-54	0.229	0.225	0.286	0.225	0.223	0.289
	(0.420)	(0.418)	(0.452)	(0.417)	(0.416)	(0.453)
Age 55-64	0.105	0.113	0.156	0.101	0.107	0.169
	(0.306)	(0.316)	(0.363)	(0.302)	(0.309)	(0.375)
Female	0.356	0.386	0.415	0.360	0.393	0.407
	(0.479)	(0.487)	(0.493)	(0.480)	(0.488)	(0.491)

Black	0.098	0.102	0.090	0.096	0.101	0.087
	(0.297)	(0.303)	(0.286)	(0.295)	(0.301)	(0.282)
Hispanic	0.138	0.140	0.110	0.140	0.143	0.112
	(0.345)	(0.347)	(0.312)	(0.347)	(0.350)	(0.316)
Other race	0.056	0.059	0.057	0.055	0.058	0.059
	(0.230)	(0.235)	(0.233)	(0.228)	(0.233)	(0.235)
Educ: Dropout	0.094	0.105	0.068	0.093	0.106	0.068
	(0.292)	(0.307)	(0.251)	(0.291)	(0.308)	(0.252)
Educ: Assoc Deg	0.109	0.106	0.103	0.110	0.108	0.103
	(0.311)	(0.308)	(0.303)	(0.313)	(0.310)	(0.304)
Educ: Some Coll	0.204	0.206	0.171	0.205	0.211	0.170
	(0.403)	(0.405)	(0.376)	(0.404)	(0.408)	(0.375)
Educ: Coll Grad	0.280	0.239	0.342	0.282	0.238	0.341
	(0.449)	(0.427)	(0.474)	(0.450)	(0.426)	(0.474)
Change in Log Earnings				-0.067	-0.073	0.021
				(0.429)	(0.418)	(0.447)
Change in Log Earnings, Occ Switchers				-0.093	-0.096	0.023
				(0.451)	(0.436)	(0.462)
Obs	17,776	6,756	2,654,241	14,358	5,371	420,552

See text for details.

Table 7: Job Rank and Skill Change Regressions: 2SLS Estimates, Rank Sample

	Rank Change Models			Skill Change Models		
	(1)	(2)	(3)	(4)	(5)	(6)
	Disp	PlClose	Non-Disp	Disp	PlClose	Non-Disp
Lost Job Occ. Rank	-0.1093	-0.1337	-0.0073	-0.0000	-0.0001	0.0000
	(0.0450)	(0.0592)	(0.0030)	(0.0001)	(0.0001)	(0.0000)
Lost Job Skill	8.3282	8.6193	0.1992	-0.1376	-0.1021	-0.0123
	(2.8403)	(3.2810)	(0.0987)	(0.0388)	(0.0499)	(0.0023)
Angular Separation	0.6020	0.5714	0.5804	0.0001	0.0001	0.0007
	(0.0573)	(0.0876)	(0.0705)	(0.0002)	(0.0002)	(0.0002)
× Occ Rank	-1.0211	-0.9673	-0.8909			
	(0.0987)	(0.1303)	(0.1416)			
× Job Skill				-0.0080	-0.0089	-0.0060
				(0.0008)	(0.0012)	(0.0008)
Tenure 1-3 Years	0.7016	1.5014		0.0042	-0.0039	
	(0.4453)	(0.7918)		(0.0028)	(0.0055)	
Tenure 3-10 Years	1.4713	2.0765		0.0032	-0.0035	
	(0.4147)	(0.7530)		(0.0033)	(0.0058)	
Tenure 11-20 Years	1.3118	1.6665		-0.0004	-0.0102	
	(0.6482)	(1.0363)		(0.0041)	(0.0076)	
Tenure 20+ Years	1.1080	2.8069		-0.0010	-0.0070	
	(0.7889)	(1.1724)		(0.0051)	(0.0072)	
Age 20-24	-3.7516	-2.1406	-0.3726	-0.0255	-0.0268	-0.0025
	(0.8214)	(1.4623)	(0.0536)	(0.0046)	(0.0075)	(0.0003)
Age 25-34	-0.2826	-0.1536	-0.0707	-0.0053	-0.0048	-0.0004
	(0.4069)	(0.6103)	(0.0148)	(0.0030)	(0.0045)	(0.0001)
Age 45-54	-0.1554	0.3000	0.0078	-0.0028	-0.0035	0.0000
	(0.4178)	(0.6317)	(0.0086)	(0.0025)	(0.0038)	(0.0001)
Age 55-64	-0.6638	-1.4620	0.0047	-0.0066	-0.0158	0.0001
	(0.5475)	(0.8034)	(0.0140)	(0.0033)	(0.0048)	(0.0001)
Educ: Dropout	-1.3624	-1.7196	-0.1022	-0.0210	-0.0225	-0.0015
	(0.6980)	(1.0087)	(0.0225)	(0.0046)	(0.0067)	(0.0002)
Educ: Assoc Deg	2.1513	2.1953	0.1163	0.0491	0.0441	0.0025
	(0.6772)	(1.1224)	(0.0230)	(0.0041)	(0.0054)	(0.0002)
Educ: Some Coll	-0.0309	-0.2046	0.0523	0.0278	0.0303	0.0016
	(0.5205)	(0.7208)	(0.0134)	(0.0033)	(0.0051)	(0.0001)
Educ: Coll Grad	2.0698	2.2547	0.1095	0.0928	0.0925	0.0052
	(0.8726)	(1.1316)	(0.0301)	(0.0049)	(0.0064)	(0.0002)
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17763	6750	2869201	17763	6750	2869201
Cragg-Donald	488.4	167.4	829.3	376.8	120.4	858.4
Kleibergen-Paap	139.6	90.86	35.63	95.21	40.38	18.62
R-Square	.4075	.4082	.3613	.4478	.4578	.3222

This Table contains selected coefficients for 2SLS estimates of Equation 25 in columns 1-3, and of its skill analog in columns 4-6. The sample of displaced workers includes those who did not report earnings, while the sample of non-displaced workers is taken from rotations 2-4 and 6-8 of the monthly CPS data. Angular Separation and its interactions with lost job rank and skill are endogenous, with instruments for displaced (non-displaced) workers equal to occupation-specific means for workers in the non-displaced (displaced) sample. Standard errors clustered on 1990 occupation are contained in parentheses.

Table 8: Predicted Effects of Changes in Lost Job Rank, Skill, and Skill Composition

	Rank Change Models			Skill Change Models		
	Displ	PlantCl	NonDispl	Displ	PlantCl	NonDisp
A. 2SLS Estimates, Job Rank Samples						
	Effect of Standard Deviation Change in Rank or Skill					
Low Ang Sep	-3.19	-3.82	-0.46	-0.03	-0.02	-0.00
	(1.16)	(1.52)	(0.04)	(0.01)	(0.01)	(0.00)
Mean Ang Sep	-14.44	-14.48	-10.28	-0.10	-0.10	-0.05
	(0.42)	(0.52)	(1.53)	(0.00)	(0.00)	(0.01)
High Ang Sep	-25.70	-25.14	-20.10	-0.16	-0.17	-0.10
	(1.18)	(1.53)	(3.09)	(0.01)	(0.01)	(0.01)
	Effect of Standard Deviation Change in Angular Separation					
Low Rank/Skill	11.57	11.01	12.40	0.06	0.07	0.08
	(1.41)	(2.27)	(1.64)	(0.01)	(0.02)	(0.01)
Mean Rank/Skill	0.32	0.35	2.58	-0.00	-0.00	0.03
	(1.21)	(1.69)	(1.76)	(0.01)	(0.01)	(0.01)
High Rank/Skill	-10.94	-10.31	-7.23	-0.07	-0.08	-0.02
	(1.83)	(2.16)	(2.89)	(0.01)	(0.01)	(0.01)
B. 3SLS Estimates, Earnings Samples						
	Effect of Standard Deviation Change in Rank or Skill					
Low Ang Sep	-4.05	-3.44	-2.47	-0.03	-0.03	-0.03
	(1.15)	(1.74)	(0.91)	(0.01)	(0.01)	(0.00)
Mean Ang Sep	-14.48	-14.33	-12.75	-0.10	-0.10	-0.08
	(0.40)	(0.60)	(0.64)	(0.00)	(0.00)	(0.00)
High Ang Sep	-24.91	-25.21	-23.04	-0.17	-0.17	-0.14
	(1.13)	(1.60)	(2.05)	(0.01)	(0.01)	(0.01)
	Effect of Standard Deviation Change in Angular Separation					
Low Rank/Skill	10.44	11.51	12.08	0.07	0.07	0.07
	(1.57)	(2.17)	(1.66)	(0.01)	(0.02)	(0.01)
Mean Rank/Skill	0.01	0.62	1.79	-0.00	-0.00	0.02
	(1.40)	(1.95)	(1.45)	(0.01)	(0.01)	(0.01)
High Rank/Skill	-10.42	-10.26	-8.49	-0.07	-0.07	-0.04
	(1.93)	(2.79)	(2.38)	(0.01)	(0.01)	(0.01)

Results in Part A are based on 2SLS estimates from Table 7. Results in Part B are based on 3SLS estimates from Table A1. Standard errors clustered on IPUMS 3-digit occupation (1990) are in parentheses.

Table 9: Wage Changes by Lost Job Rank Decile

	All			Occupation Switchers		
Decile	Displ	Plant Cl	Non-Disp	Displ	Plant Cl	Non-Disp
1	-0.0393	-0.0478	0.0191	-0.0762	-0.0646	0.0225
2	-0.0370	-0.0870	0.0214	-0.0675	-0.1137	0.0353
3	-0.0102	0.0001	0.0370	-0.0146	-0.0152	0.0508
4	-0.0411	-0.0322	0.0293	-0.0390	-0.0339	0.0450
5	-0.0595	-0.0272	0.0264	-0.0535	-0.0186	0.0464
6	-0.0693	-0.0537	0.0305	-0.0737	-0.0430	0.0356
7	-0.0778	-0.1004	0.0176	-0.1151	-0.1276	0.0167
8	-0.0977	-0.1023	0.0165	-0.1383	-0.1461	0.0083
9	-0.0806	-0.1045	0.0170	-0.1279	-0.1319	0.0129
10	-0.1211	-0.1075	0.0107	-0.1561	-0.1565	-0.0026

These data show mean log earnings changes between the current and last/lost job.

Table 10: Wage Change Regressions: 3SLS Estimates

	Dipslaced		Non-Displaced
	(1)	(2)	(3)
	All	PlantCl	Priv
$\Delta Rank$	0.0012	0.0016	0.0004
	(0.0004)	(0.0004)	(0.0002)
$\Delta Skill$	0.2077	0.2618	0.1985
	(0.0565)	(0.0638)	(0.0181)
Tenure 1-3 Years	0.0150	0.0285	
	(0.0107)	(0.0188)	
Tenure 3-10 Years	-0.0358	-0.0205	
	(0.0122)	(0.0199)	
Tenure 11-20 Years	-0.1155	-0.0939	
	(0.0157)	(0.0209)	
Tenure 20+ Years	-0.1229	-0.1064	
	(0.0203)	(0.0332)	
Displaced 1 Year Ago	-0.0045	0.0130	
	(0.0090)	(0.0139)	
Displaced 3 Years Ago	0.0023	0.0154	
	(0.0088)	(0.0129)	
Age 20-24	0.0898	0.0812	0.0300
	(0.0135)	(0.0216)	(0.0034)
Age 25-34	0.0412	0.0390	0.0176
	(0.0080)	(0.0149)	(0.0023)
Age 45-54	-0.0209	-0.0229	-0.0119
	(0.0110)	(0.0121)	(0.0019)
Age 55-64	-0.0423	-0.0366	-0.0160
	(0.0143)	(0.0192)	(0.0021)
Educ: Dropout	-0.0128	-0.0204	0.0008
	(0.0123)	(0.0150)	(0.0027)
Educ: Assoc Deg	0.0112	0.0199	0.0081
	(0.0133)	(0.0204)	(0.0027)
Educ: Some Coll	-0.0118	0.0044	0.0042
	(0.0099)	(0.0156)	(0.0019)
Educ: Coll Grad	0.0208	0.0320	0.0080
	(0.0108)	(0.0163)	(0.0023)
Year Effects	Yes	Yes	Yes
Demographics	Yes	Yes	Yes
Observations	14346	6139	421492
R-Square	.05684	.05329	.007964

This Table contains selected coefficients for 3SLS estimates of Equation 30. The samples of both displaced and non-displaced workers are taken from the outgoing (4 and 8) rotations the monthly CPS data. Both ΔRNK and $\Delta Skill$ are endogenous. See the notes to Table 7. Standard errors clustered on 1990 occupation are contained in parentheses.

Table 11: Predicted Effects of Lost/Last Job Rank and Skill on Real Wages

	Displ	PlantCl	NonDispl
Std. Dev. Change in Rank			
low Ang Sep	-0.005	-0.006	-0.001
	(0.002)	(0.004)	(0.001)
med Ang Sep	-0.017	-0.024	-0.005
	(0.005)	(0.006)	(0.002)
high Ang Sep	-0.029	-0.041	-0.009
	(0.009)	(0.010)	(0.004)
Std. Dev. Change in Skill			
low Ang Sep	-0.004	-0.004	-0.005
	(0.002)	(0.003)	(0.001)
med Ang Sep	-0.018	-0.023	-0.016
	(0.005)	(0.006)	(0.002)
high Ang Sep	-0.033	-0.042	-0.027
	(0.009)	(0.011)	(0.003)

Results are based on 3SLS estimates from Tables A1 and 10. Standard errors clustered on occupation are in parentheses.

Table 12: Predicted Effects of Angular Separation on Real Wages

	Displ	PlantCl	NonDispl
Via Both RNK and Skill Change Equations			
low Rank and Skill	0.026	0.037	0.019
	(0.007)	(0.009)	(0.004)
med Rank and Skill	-0.000	0.001	0.004
	(0.002)	(0.004)	(0.001)
high Rank and Skill	-0.027	-0.036	-0.011
	(0.007)	(0.007)	(0.003)
Via Change in Rank			
low Rank	0.012	0.018	0.005
	(0.004)	(0.006)	(0.002)
med Rank	0.000	0.001	0.001
	(0.002)	(0.003)	(0.001)
high Rank	-0.012	-0.016	-0.003
	(0.005)	(0.005)	(0.002)
Via Change in Skill			
low Skill	0.014	0.018	0.015
	(0.005)	(0.007)	(0.002)
med Skill	-0.000	-0.000	0.004
	(0.002)	(0.003)	(0.001)
high Skill	-0.015	-0.019	-0.008
	(0.004)	(0.005)	(0.002)

Results are based on 3SLS estimates from Tables A1 and 10.
Standard errors clustered on occupation are in parentheses.

Table 13: Regression of Angular Separation On Lost/Last Job Rank: Individual Level Data

	Occupation Change			Angular Separation, Occ. Changers		
	(1)	(2)	(3)	(4)	(5)	(6)
	Disp	PlantCl	Non-Disp	Disp	PlantCl	Non-Disp
Lost Job Occ. Rank	0.002	0.002	-0.000	-0.121	-0.131	-0.181
	(0.001)	(0.001)	(0.000)	(0.040)	(0.056)	(0.030)
Lost Job Skill	-0.298	-0.270	-0.021	-5.783	6.765	-20.797
	(0.060)	(0.056)	(0.004)	(4.398)	(6.635)	(3.449)
Tenure 1-3 Years	-0.021	-0.029		-1.182	-1.950	
	(0.013)	(0.019)		(0.921)	(1.704)	
Tenure 3-10 Years	-0.029	-0.052		0.556	0.027	
	(0.015)	(0.020)		(1.111)	(1.793)	
Tenure 11-20 Years	0.014	-0.003		-0.043	-0.684	
	(0.019)	(0.020)		(1.374)	(2.055)	
Tenure 20+ Years	-0.024	-0.053		-0.482	-0.195	
	(0.018)	(0.024)		(1.857)	(2.520)	
Displaced 1 Year Ago	-0.039	-0.047		-0.552	-2.210	
	(0.008)	(0.012)		(0.778)	(1.297)	
Displaced 3 Years Ago	0.019	0.031		1.023	-0.326	
	(0.009)	(0.014)		(0.897)	(1.213)	
Age 20-24	0.120	0.111	0.017	3.137	4.720	7.288
	(0.019)	(0.027)	(0.001)	(1.535)	(2.349)	(1.662)
Age 25-34	0.042	0.033	0.003	2.167	2.927	2.444
	(0.010)	(0.017)	(0.000)	(0.759)	(1.344)	(0.630)
Age 45-54	-0.008	-0.009	-0.001	-1.662	-2.250	-0.279
	(0.012)	(0.017)	(0.000)	(0.785)	(1.525)	(0.303)
Age 55-64	-0.034	-0.050	-0.004	-1.706	-1.312	-1.101
	(0.014)	(0.020)	(0.001)	(0.972)	(1.878)	(0.601)
female	0.042	0.035	-0.002	-0.416	-0.035	-0.866
	(0.020)	(0.021)	(0.002)	(1.447)	(1.788)	(1.212)
black	0.007	-0.005	0.013	0.762	2.344	6.432
	(0.016)	(0.026)	(0.001)	(1.251)	(1.694)	(1.549)
hisp	-0.048	-0.022	0.012	-2.713	0.449	3.057
	(0.013)	(0.020)	(0.001)	(1.072)	(1.686)	(1.261)
other	-0.051	-0.039	0.008	-3.083	0.193	5.033
	(0.021)	(0.030)	(0.001)	(1.600)	(2.582)	(1.166)
Educ: Dropout	-0.056	-0.069	-0.002	-6.088	-4.508	-8.037
	(0.017)	(0.025)	(0.001)	(1.528)	(2.337)	(0.816)
Educ: Assoc Deg	-0.002	-0.001	-0.001	0.201	0.333	3.414
	(0.021)	(0.023)	(0.001)	(1.486)	(1.965)	(1.063)
Educ: Some Coll	0.012	-0.007	0.002	1.656	1.816	2.581
	(0.011)	(0.017)	(0.001)	(1.204)	(1.500)	(1.025)
Educ: Coll Grad	0.009	-0.027	0.004	-12.320	-14.078	-6.342
	(0.023)	(0.026)	(0.001)	(2.261)	(2.871)	(1.934)
Constant	0.545	0.540	0.031	79.425	82.522	2.367
	(0.047)	(0.047)	(0.004)	(4.170)	(5.874)	(16.542)
Years	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17779	6758	2874398	17766	6752	2869603
R-Square	.03337	.03564	.003378			
ρ				.1853	.1174	.7484
σ				33.32	33.08	46.8

Robust standard errors in parentheses.

Table A1: Job Rank and Skill Change Regressions: 3SLS Estimates, Earnings Sample

	Rank Change Models			Skill Change Models		
	AllDisp	PlantC	Non-Displaced	AllDisp	PlantC	Non-Displaced
Lost Job Occ. Rank	-0.1284	-0.0865	-0.0829	-0.0000	-0.0001	0.0000
	(0.0459)	(0.0652)	(0.0361)	(0.0001)	(0.0001)	(0.0001)
Lost Job Skill	8.7268	9.5928	2.1096	-0.1161	-0.1083	-0.1222
	(2.4479)	(3.2881)	(1.1956)	(0.0533)	(0.0578)	(0.0231)
Angular Separation	0.5673	0.6543	0.5863	0.0006	0.0005	0.0006
	(0.0544)	(0.1055)	(0.0724)	(0.0003)	(0.0003)	(0.0001)
× Occ Rank	-0.9628	-1.0492	-0.9329			
	(0.0987)	(0.1432)	(0.1317)			
× Job Skill				-0.0084	-0.0088	-0.0067
				(0.0011)	(0.0013)	(0.0008)
Tenure 1-3 Years	0.8707	1.6437		0.0047	-0.0053	
	(0.5319)	(0.9131)		(0.0035)	(0.0057)	
Tenure 3-10 Years	1.5199	2.4752		0.0052	-0.0015	
	(0.4350)	(0.8770)		(0.0035)	(0.0053)	
Tenure 11-20 Years	1.0104	1.2487		-0.0006	-0.0130	
	(0.7806)	(1.0335)		(0.0049)	(0.0074)	
Tenure 20+ Years	1.3933	2.7410		0.0017	0.0005	
	(0.9950)	(1.4997)		(0.0066)	(0.0094)	
Age 20-24	-3.6460	-2.7768	-3.0460	-0.0281	-0.0301	-0.0186
	(0.7936)	(1.4951)	(0.3418)	(0.0055)	(0.0083)	(0.0021)
Age 25-34	-0.3826	-0.6397	-0.7327	-0.0054	-0.0047	-0.0036
	(0.4387)	(0.8353)	(0.1178)	(0.0035)	(0.0047)	(0.0007)
Age 45-54	-0.0593	-0.4930	0.0366	-0.0024	-0.0042	0.0000
	(0.4754)	(0.7601)	(0.0811)	(0.0028)	(0.0041)	(0.0006)
Age 55-64	-0.3267	-1.8776	-0.2282	-0.0054	-0.0153	-0.0005
	(0.5630)	(1.0191)	(0.1280)	(0.0038)	(0.0055)	(0.0008)
Educ: Dropout	-1.6810	-1.2856	-1.0942	-0.0166	-0.0187	-0.0183
	(0.7538)	(1.1001)	(0.2633)	(0.0060)	(0.0076)	(0.0022)
Educ: Assoc Deg	2.8942	2.3345	1.4612	0.0537	0.0475	0.0292
	(0.6799)	(1.1341)	(0.3083)	(0.0044)	(0.0063)	(0.0018)
Educ: Some Coll	0.1808	0.3378	0.5674	0.0286	0.0327	0.0180
	(0.6112)	(0.8696)	(0.1939)	(0.0037)	(0.0067)	(0.0009)
Educ: Coll Grad	3.2832	2.3928	1.5015	0.0998	0.1012	0.0590
	(0.9869)	(1.2905)	(0.4767)	(0.0064)	(0.0068)	(0.0030)
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13796	5924	420032	13796	5924	420032
R-Square	.409	.3878	.3692	.4204	.4399	.3886

This Table contains selected coefficients for 3SLS estimates of Equation 25 in columns 1-3, and of its skill analog in columns 4-6. Angular Separation and its interactions with lost job rank and skill are endogenous, with instruments for displaced (non-displaced) workers equal to occupation-specific means for workers in the non-displaced (displaced) sample. Both the displaced and non-displaced samples are taken from the outgoing rotations (4 and 8) of the monthly CPS data. Standard errors clustered on 1990 occupation are contained in parentheses.