The Effect of Career Displacement: A Task-Specific Human Capital Approach

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Abstract

Most research finds that changes in occupational tasks between the lost and new job harm career outcomes of displaced workers. We devise a model and show empirically using data on skill, occupational wage percentile, and wages from the 1994-2018 Displaced Worker Surveys that such changes interact with rank on the lost job, harming workers displaced from higher-rank jobs, but can benefit workers displaced from lower-rank jobs. We deal with potential simultaneity bias using instruments derived from continuously employed workers. The success of those instruments suggests that the career transitions of displaced workers roughly mimic those of non-displaced workers.

JEL Codes: J62, J63, J64
Keywords: Task-Specific Human Capital; Displaced Workers

Abbrevations

CO, Comparison Sample; CE, Continuously Employed; CPS, Current Population Survey; DOT, Dictionary of Occupational Titles; IV, Instrumental Variables; IPUMS, Integrated Public Use Microdata Series; NC, Non-Plant Closure; OLS, Ordinary Least Squares; SNAG, South Carolina, North Carolina, Alabama, Georgia; UI, Unemployment Insurance.

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1 Introduction

Researchers have long interpreted the earnings losses of displaced workers as evidence of lost specific human capital. That losses are higher for workers displaced from longer tenure jobs is consistent with the loss of human capital specific to the firm (Fallick, 1996), but workers who found employment in their old industry tended to fare better, suggesting that human capital is partly portable across firms (Carrington, 1993). The most recent evidence suggests that firm-specific factors play a minor role (Lachowska et al., 2020).

Occupation-specific human capital, on the other hand, appears to be important (Kambourov and Manovskii, 2009). Earnings losses are smaller not only for those who find new jobs in their old occupation, but among those who switch occupations, for those whose new jobs use skills similar to those of the old (Poletaev and Robinson, 2008; Robinson, 2018). 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). In the task-specific framework, displaced workers suffer earnings losses when they accept new jobs that employ skills in proportions different than the ones they left.

We refer to such changes in skill proportions as "skill composition change." Recently, Robinson (2018) found that the negative effects of skill composition change were limited to workers who moved to less-skilled jobs. This is important, because not all displaced workers move to lower-rank, lower wage jobs (Forsythe, 2017; Huckfeldt, 2016; Farber, 2017). Indeed, Gathmann and Schönberg (2010) present evidence that greater levels of skill composition change *increase* earnings for workers who lose the lowest-wage jobs, while decreasing earnings for workers who lose higher-wage jobs. The findings of Robinson (2018) and Gathmann and Schönberg (2010) would be consistent with one another if workers who lose higher-wage jobs are more likely to move to lower-skill jobs.

Our key contribution is to show, using the task-specific human capital framework, that skill composition change and changes in rank between the lost and new job are closely linked. We characterize career trajectories by two components: (1) the composition of skills and (2) hierarchical rank, where rank is synonymous with human capital accumulated to date. Skills are portable across jobs, but the combinations in which firms use those skills differ (Lazear, 2009). The jobs for which workers who lose higher-rank jobs are qualified are limited by their "scarce skill." This is consistent with the argument in Gathmann and Schönberg (2010) that occupational switches become increasingly costly as workers age, that is, as they acquire task-specific human capital. However, we go a step further and show that a *given* degree of task change is more deleterious, the higher the rank of the lost job.

By contrast, workers who lose jobs at the lower end of the skill spectrum can benefit by accepting jobs different from the one they lost when those jobs make fuller use of the worker's skill portfolio, which we call "career trajectory upgrade." Acquiring new skills – called "skill-broadening"

– is essential for workers to move up the career ladder (Frederiksen et al., 2016; Frederiksen and Kato, 2017). However, because mobility is costly, workers are not always employed in jobs that make full use of their skills at every point in time (Farber, 2017). For workers displaced from lower-rank jobs, greater skill composition change is – up to a point – beneficial.

There are competing approaches for examining the labor market outcomes of displaced workers. For example Blien et al. (2019) found that among workers displaced from routine-manual jobs, more able workers were more likely to switch to non-routine jobs and enjoyed faster long-run wage growth. The augmented task-specific approach used here is stylized and ignores the details of the particular types of skills used. What is gained, though, is an understanding of how changes in the composition of skills as measured in prior research translate into labor market outcomes.

Another distinguishing feature of our analysis is its examination of job rank in addition to earnings. Garg (2016) showed that workers displaced from jobs higher in the occupational wage distribution tended to experience reductions in rank between the lost and new job, and workers displaced from jobs low in the distribution, increases in job rank. However, such a pattern is consistent with mere reversion to the mean. Such "mean reversion" is a feature of the task-specific approach in that workers who lose higher-rank jobs tend to move farther downward in rank, conditional on the degree of skill composition change. However, the task-specific approach goes farther: the effects of lost job rank are more negative, the greater the degree of skill composition change, for workers beyond the skill-broadening stage.

We test the implications of the model using data on rank and earnings for full-time workers from the 1994-2018 Displaced Workers Surveys. We use two occupation-based measures of job rank. The first is the occupational wage percentile (Autor and Dorn, 2014; Forsythe, 2017) and the second is the occupation's vector of skills derived from the Dictionary of Occupational Titles (DOT) (Poletaev and Robinson, 2008; Robinson, 2018). The angle between the skill vectors, used by Gathmann and Schönberg (2010), emerges naturally within the task-specific framework as a measure of skill composition change. We also account for the potential endogeneity of skill composition change, which to our knowledge has not been attempted in the displaced worker literature. In most cases, occupation-specific mean values of skill composition change for continuously employed workers do a good job of instrumenting for the skill composition changes of displaced workers, suggesting that the career transitions of displaced workers produce results that roughly – perhaps only very roughly – mimic those of non-displaced workers.

To foreshadow our findings, our preferred estimates imply that for displaced workers as a whole each standard deviation increase in skill composition change translates into a 0.12-0.33 standard deviation *increase* in rank for workers displaced from low-rank jobs, and a 0.26-0.52 standard deviation *decrease* for workers displaced from high-rank jobs, depending on rank measure. We also estimate the effects of skill composition change on wages. Our preferred estimates imply that a standard deviation increase in skill composition change leads to a 0.2 log point increase in wages for workers displaced from lowest-wage jobs, and a 0.17 log point decrease in wages for workers displaced from high-wage jobs.

The paper is organized as follows. Section 2 introduces our data, and Section 3, our measures of rank, and our measures of skill composition change. Section 4 examines career transitions in a qualitative fashion and motivates the theoretical model summarized in Section 5. We examine empirically changes in job rank in Section 6, and changes in wages in Section 7. Section 8 concludes the paper with a brief recap and suggestions for future research.

2 The Data

2.1 Displaced Worker Samples from the Current Population Survey

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) (Flood et al., 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 is small compared to the losses of workers who are newly employed in part-time jobs. We start our analysis with 1994, the first year in which it is possible to identify such workers, and end with the 2018 sample year.

In addition to occupation and earnings on the lost job, the Displaced Worker Surveys contain a variety of useful information, including full time status (our sample contains only those who worked full time on both the lost and new job), class of worker (our sample contains only those working for private employers), tenure on the lost job, and information on unemployment arising from displacement (weeks looking, unemployment benefit receipt and exhaustion).

2.2 Displaced and Plant Closure Samples

Although workers displaced from their jobs did not separate voluntarily and were not terminated for cause, much research distinguishes between displaced workers as a whole, and workers displaced due to a plant closure, the latter on the grounds that the case for exogenous separation is most clear. We therefore carry out our analysis on both the sample of displaced workers as a whole, called the Displaced Sample, and on the subsample of those displaced due to a plant closure, called the Plant Closure Sample. The pattern of results obtained from the Plant Closure sample is similar to that obtained using the Displaced Sample, but the estimates, especially instrumental variables (IV) estimates, are less precise. We also make limited use of a sample of those displaced for reasons other than plant closure, called the Non-Plant Closure Sample.

2.3 Comparison Samples

Like Robinson (2018), we make use of a comparison sample of full-time, privately employed workers using the monthly CPS data. The Rank Sample uses data on rotations 2-4 and 6-8, for which the Census Bureau uses dependent coding procedures for occupation in order to reduce spurious switches. The Earnings Sample is limited to respondents in the outgoing rotations (4 and 8), precluding the use of dependently coded occupation data. These data are used to construct instruments for the Displaced and Plant Closure samples, but are also used for estimation purposes as a point of comparison.

Although relatively few workers are displaced in month-to-month employment transitions, it cannot be ruled out when the displacement question is not asked. However, month-to-month job transitions within a firm, identifiable in rotations 2-4 and 6-8 since the CPS began dependently coding information on employment, not only involve no displacement, but reflect mutually agreed, within-firm career transitions. These transitions comprise the Continuously Employed (CE) Sample, our primary source of comparison data. We also construct, for limited purposes, a subsample of the Comparison Sample that contains only truly non-displaced workers.[1]

2.4 Dictionary of Occupational Titles

Like Robinson (2018), we characterize the skill composition of occupations using data 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.[2] Following Poletaev and Robinson (2008) and Robinson (2018), we use factor analysis to reduce these nearly 50 characteristics to $N = 5$ skill factors for each occupation j, denoted by $S_{jn}, n = 1, ..., 5$, rotated according to the varimax method, using data from the March 1982-2018 CPS data, applying the supplement weight.[3] The DOT scores are matched to the individual-level CPS data by 3-digit (1990s) and 4-digit (2000s and 2010s) occupation and gender.

3 Measuring Rank and Skill Composition Change

Our paper examines the consequences of skill composition change as a function of career trajectory. We therefore require measures of (1) skill composition change; and (2) position in the career hierarchy.

3.1 Measuring Rank

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." While information on hierarchical rank is not available in the data sets most commonly used to study displaced workers, information on occupation *is*. In our model, we identify rank with human capital, and empirically, we have two occupation-based measures of rank: skill defined as a weighted sum of occupational characteristics, where the weights are derived from an auxiliary wage equation; and the occupational wage percentile. Finally, we analyze the log wage itself. We think that the characterization of these measures as "rank" is reasonable for two reasons. First, most theories of career trajectory associate advancement with acquisition of human capital. Second, the word "rank" conveys the notion that workers do not continuously advance as they acquire human capital into positions that make full use of their skill portfolio, but must often wait to be promoted. It therefore captures the notion of mobility costs invoked by Farber (2017) in his explanation for why earnings increase for a substantial fraction of displaced workers between the lost and new job.

3.1 Occupational Wage Percentile

The occupational wage percentile was first used by Autor and Dorn (2014) to characterize occupational skill and recently used by Groes et al. (2014), Garg (2016), Huckfeldt (2016), and Forsythe (2017) as a measure of occupational rank. However, a worker's career status is affected by factors other than just occupation, including age, education, and industry composition of the occupation. We therefore focus on rank measures that are corrected for other individual characteristics. In particular, we estimate a log wage regression using March CPS data as a function of regressors that include vectors of schooling, potential labor market experience, and a vector of demographic controls, a vector of 3-digit IPUMS 1990 industry dummy variables, and a vector of 3-digit IPUMS 1990 occupation dummy variables.[4] Letting $\hat{\omega}_j$ denote the estimated coefficient on the indicator for occupation ("job") j, our occupational wage percentile-based measure of job rank for job j is

$$PCT_j \equiv F(\hat{\omega}_j), \tag{1}$$

where $F(\hat{\omega}_j)$ is the value of cumulative distribution function in the sample. Although we focus on this adjusted measure, plausible arguments can be made for use of an unadjusted rank measure based on the raw wage percentile. We therefore carry out analysis using the unadjusted measure as well, most of which is contained in Appendix G so as not to overwhelm the reader.

3.1 A DOT-Based Measure

The second measure of job rank, commonly used in the study of displaced workers, including Robinson (2018), is the weighted sum of skill components S_{jn},

$$SKL_j \equiv \sum_{n=1}^{N} \hat{\beta}_n S_{jn}, \tag{2}$$

where $\hat{\beta}_1, ...\hat{\beta}_N$ is a vector of weights. The $\hat{\beta}_n$ are estimated via a second log wage equation using the above-mentioned March CPS data, and include the $N = 5$ skill factors in place of the industry and occupation dummies. As in the case of the PCT, we present a number of results using an unadjusted measure of SKL, contained mostly in Appendix G.

To reduce clutter, we relegate to Appendix A detailed description of the measures of rank, including an analysis of life cycle patterns similar to the one in Yamaguchi (2012). While neither is ideal and each has its peculiarities, both seem, broadly speaking if not in every detail, "reasonable."

3.1 Wages

The empirical analysis of wages focuses on models that capture the effect of lost job rank via the lost job wage. Like the skill-based measures, wages are not a perfect measure of rank, reflecting, for example, hedonic differences in the non-wage characteristics of the job. However, wages do have the advantage of reflecting differences within as well as between occupations, and, unlike SKL, capture non-linear interactions between the S_{jn}.

3.2 Measuring Skill Composition Change: Angular Separation

The Angular Separation between skill vectors on the lost and new job (Gathmann and Schönberg, 2010) will be seen to emerge as a natural measure of skill composition change. Let S_{ln} and and S_{cn} denote levels of the nth DOT-based skill component required in the lost (or, for non-displaced workers, last) job and the current job, $n = 1,...N$. The Angular Separation between skill vectors is

$$ANGL \equiv \arccos\{\frac{\sum_{n=1}^{N} S_{ln} \times S_{cn}}{\left(\sum_{n=1}^{N} S_{ln}^2\right)^{1/2}\left(\sum_{n=1}^{N} S_{cn}^2\right)^{1/2}}\} \times 180°/\pi, \tag{3}$$

where the expression in braces is the cosine measure of similarity between the two jobs, which ranges from -1 to 1, $N = 5$, and where $ANGL$ ranges from 0° to 180°.[5]

4 Empirical Overview of Career Transitions

Before turning to the formal model, we examine empirical patterns in the data. We focus on the adjusted rank measures in the body of the paper and present results for the unadjusted measures in Appendix G. For the purposes of exposition, it is understood that references to PCT and SKL refer to the adjusted measures.

Occupation Switching Gathmann and Schönberg (2010) predicted that older workers, with more task-specific human capital, should be less likely to switch occupation. Column 1 of Table 1 shows the fraction of workers who switch occupations as a function of rank decile: PCT decile in Part A, SKL decile in Part B, and real wage decile in Part C. Although the fraction of workers who switch occupations is, if anything, positively related to PCT decile, it is negatively related to both SKL and real wage decile.[6]

The propensity to switch occupations is not unique to displaced workers. It is positively related at the occupation level to the month-to-month fraction switching occupation in (1) the Continuously Employed Sample, seen on the top left-hand-side of Figure 1, and (2) among employer switchers in the Non-Displaced Sample, seen on the right-hand-side. These correlations suggest that similar economic forces may be at work for displaced and non-displaced workers, albeit at different scales.

Changes in Skill Composition A corollary of Gathmann and Schönberg (2010) is that conditional on switching occupation, workers displaced from higher-rank jobs should try harder to find jobs that use skills similar to those used on the old job. Indeed, skill composition change – career trajectory upgrade – can benefit those who lose lower-rank jobs by enabling them to more fully exploit their skill portfolio (Lazear, 2009; Frederiksen et al., 2016; Gibbons and Waldman, 2004). The degree of skill composition change as measured by $ANGL$ (col. 6) is roughly inverted U-shaped in rank decile, rising gently through the first three (PCT and wage) and four (SKL) deciles, mostly declining thereafter, and smaller at the highest deciles than at lower deciles.

Skill Broadening and Task Specificity The task specificity story suggests that higher-rank job losers who avoid moving to lower-rank jobs are those who find jobs more similar to the one they lost, while the career trajectory upgrade story suggests that lower-rank job losers who move up in rank are those who find jobs that differ *more* from the one they lost. Table 2 contains mean values of $ANGL$ conditional on rank rising (col. 5, $\Delta R > 0$) and falling (col. 6, $\Delta R < 0$). The data are consistent with both stories. Mean values of $ANGL$ are higher for lower-rank job losers who move up in rank than for those who move down, seen in PCT deciles 1-3 and in SKL deciles 1-5, which is consistent with a skill-broadening story. At the other end of the spectrum, mean values of $ANGL$ are lower for those who move up in rank. Evidence of career trajectory upgrade by real wage decile appears to be limited to those losing jobs in wage decile 1, but is more apparent in detailed examination of the data.

Figure 2 graphs mean values of $ANGL$ as a function of the absolute difference in rank decile between the current and lost/last job for the Displaced, Plant Closure, and Continuously Employed Samples, where we distinguish between increases and declines/non-increases in rank decile.[7] There is a positive relationship between $ANGL$ and the magnitudes of rank increase and rank decrease in all three samples, indicating that neither career trajectory upgrade nor task specificity are unique to displaced workers.

Unemployment as Evidence of Search Effort We have no direct evidence, but the skill composition changes that accompany upward moves in rank are consistent with search being directed (Kudlyank and Sysuyev, 2014). Interpretation of downward moves in rank is more difficult; the earnings losses of displaced workers could reflect a decision to exert low search effort. However, Valletta (1991) found that longer tenure on the lost job, a proxy for specific human capital, was associated with longer durations of job search, and Herz (2019) found among workers with more specific training longer unemployment spells in thin markets, where mobility costs are likely to be

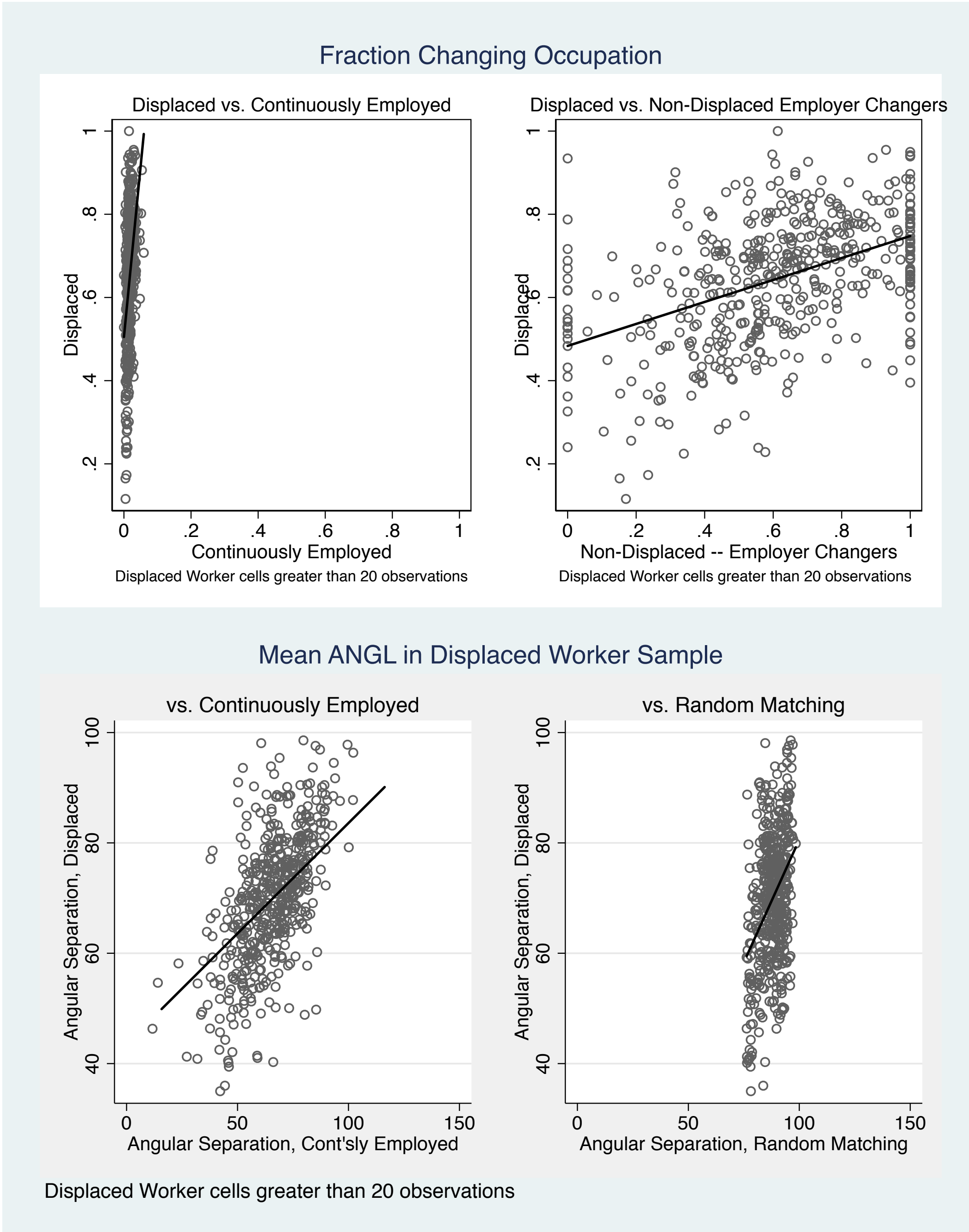

Figure 1: Fraction Changing Occupation: Displaced versus Comparison Samples

Fraction switching occupation in Displaced Sample is positively related to the month-to-month fraction switching in Continuously Employed (CE) Sample (top left) and among employer switchers in Non-Displaced Sample (top right). The horizontal scales are the same; the percentage switching in CE Sample is tiny – about 4% – relative to the Displaced Sample, about 65%. Occupation-level means of *ANGL* in the Displaced Sample are positively correlated with those in the Continuously Employed Sample (bottom left) and under random mobility (bottom right – see Section 4 for details). Horizontal scales are the same to emphasize relative lack of variation with random matching.

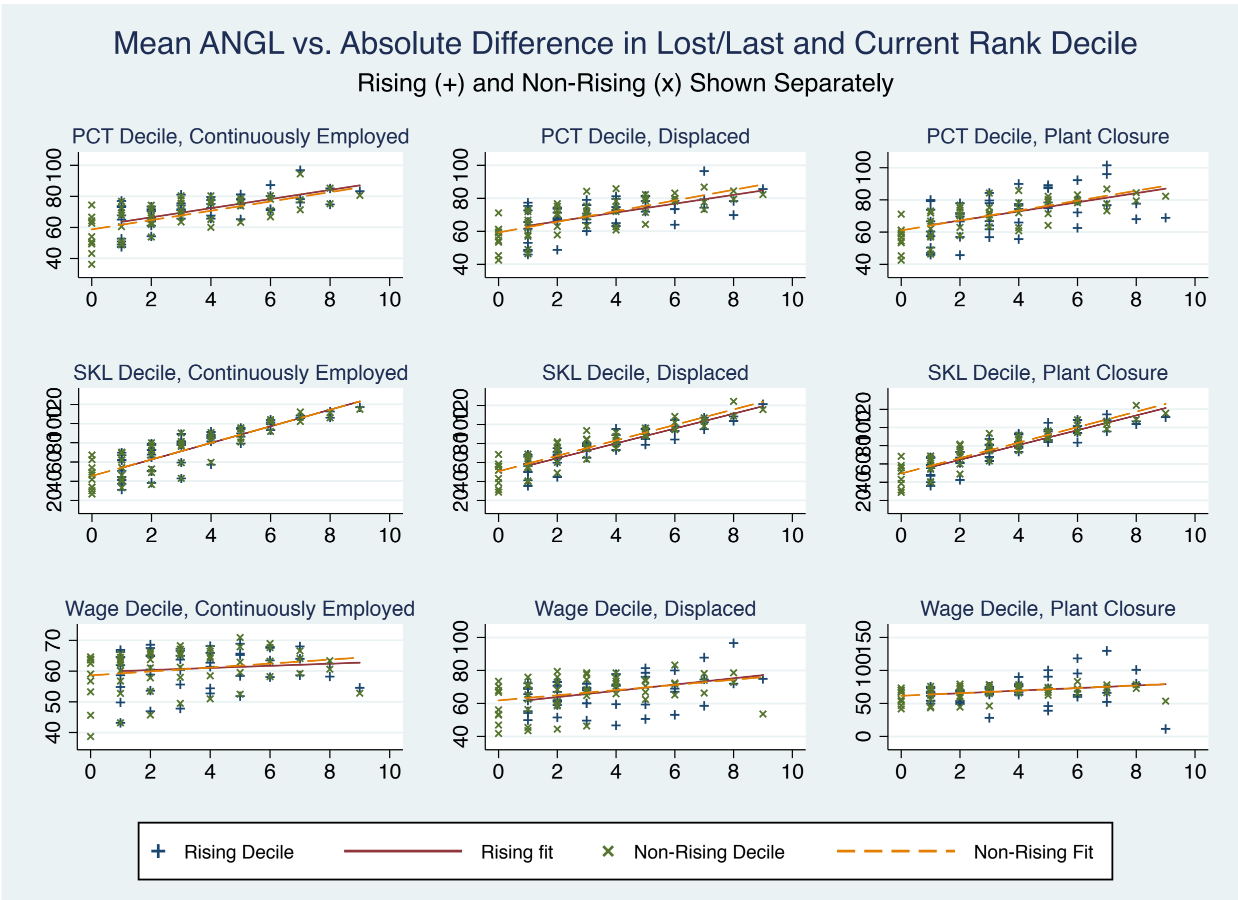

Figure 2: Mean *ANGL* Conditional on Absolute Difference Between Lost/Last and Current Job Rank Decile: Rising (+) and Non-Rising (x) Shown Separately

Based on the data reported in Table A6, this figure graphs the mean values of *ANGL* conditional on lost/last and current skill decile as a function of the absolute change in rank decile. A positive slope for upward moves in rank ("+") is evidence consistent with career trajectory upgrade, while a positive slope for downward moves and rank stayers ("x") is evidence consistent with task specificity.

high (472). Similar tendencies were observed by Faberman and Kudlyak (2019) in their analysis of on-line job applications (347). These patterns are not easily explained within the standard search framework (Valletta, 1991), but Faberman and Kudlyak (2019) observed that they are consistent with the directed search model of Salop (1973) in which workers search for jobs with the highest expected returns first.

Kudlyank and Sysuyev (2014) observed greater sorting on job education requirements at the start of search than at the end. Those displaced from more highly ranked jobs initially may try to locate new jobs similar to the old but are induced to accept different jobs as search duration lengthens. Table 1 shows that the mean duration of search (col. 4) and propensity to exhaust unemployment insurance (UI) benefits (col. 5) are increasing in PCT decile, which is consistent with this story, but decline in SKL decile and display no pattern with respect to wage decile. Table 2 shows, though, that unemployment spells tend to be longer for higher-rank job losers when rank declines than when rank rises, although the differences, reported in Appendix TableA9, are not always statistically insignificant. Correlation need not reflect causation, but the evidence is consistent with the notion that rank reductions occur despite higher, or at least not as a result of lower search effort.

Random Mobility Lower-rank job losers may tend to move up in rank, and higher-rank job losers down in rank simply due to chance. One way to infer directed search is to compare the actual values of $ANGL$ with those that would be observed under random mobility (Robinson, 2018; Gathmann and Schönberg, 2010). We calculate $ANGL$ for every possible combination of old and new occupation and calculate its expected value assuming that the probability of finding a job in an occupation is proportional to the fraction of workers in the Displaced Sample employed in that occupation, averaged over the entire period.[8] The resulting calculations are seen in Table 3, where we reproduce the means for the Displaced Sample from Table 1 and show means from the Continuously Employed Sample for comparison. Consistent with Robinson (2018), means of $ANGL$ are higher under random mobility than observed for displaced workers, even for those displaced from lower-rank jobs, for whom changes in skill composition are potentially beneficial. Notice, too, that the means for the Displaced and Continuously Employed Samples are similar. Indeed, across 901 3- and 4-digit occupations, the correlation between mean values of $ANGL$ in the Displaced and Continuously Employed Samples is 0.40, seen in the bottom left-hand graph in Figure 1. This finding is consistent with the research of Forsythe (2017), who finds that patterns of occupation change upward and downward are not unique to displaced workers.[9] This correlation could reflect that displaced workers are responding to similar, albeit not identical market forces as those not displaced.[10] This is not to say that $ANGL$ in the data and under random mobility are unrelated. A positive relationship is evident in the bottom right-hand-side of Figure 1, graphed on the same scale as the left-hand-side for comparability. However, as found by Gathmann and Schönberg (2010), the means of $ANGL$ under random mobility display far less dispersion than do real-world data.

Table 1: Means of Career Transition Variables by Lost Job Rank Decile, Displaced Worker Sample

				A. *PCT* Deciles				
			All Displaced				Occ Switchers	
Decile	Δ Occ	RANK	Δ$WAGE$	Wks Unem	Exh. UI	ANGL	Δ RANK	Δ$WAGE$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1	0.64	5.90	-0.06	11.57	0.11	70.80	41.41	-0.07
2	0.59	16.10	-0.01	11.27	0.10	71.46	33.11	-0.02
3	0.59	24.23	-0.00	10.39	0.10	75.64	26.65	-0.02
4	0.61	35.96	-0.06	11.93	0.12	69.18	15.84	-0.07
5	0.69	44.95	-0.06	14.57	0.15	70.92	8.80	-0.07
6	0.66	57.08	-0.08	12.77	0.16	65.62	-0.72	-0.09
7	0.71	66.64	-0.07	13.99	0.15	67.97	-10.76	-0.10
8	0.66	75.62	-0.08	13.28	0.14	58.13	-15.04	-0.12
9	0.67	85.98	-0.12	12.94	0.14	59.30	-22.89	-0.18
10	0.70	95.19	-0.10	13.54	0.15	65.98	-33.75	-0.13
				B. *SKL* Deciles				
1	0.77	-0.34	-0.01	14.00	0.17	66.12	0.19	-0.00
2	0.73	-0.25	-0.08	13.78	0.15	66.02	0.12	-0.09
3	0.71	-0.18	-0.01	12.56	0.12	69.19	0.09	-0.03
4	0.60	-0.12	-0.03	12.01	0.12	74.01	0.04	-0.06
5	0.69	-0.06	-0.08	13.18	0.16	71.87	0.03	-0.08
6	0.68	0.01	-0.08	13.23	0.15	71.66	-0.01	-0.11
7	0.60	0.08	-0.09	11.96	0.12	71.30	-0.08	-0.12
8	0.69	0.15	-0.09	12.96	0.14	62.71	-0.10	-0.12
9	0.63	0.22	-0.12	12.55	0.12	58.53	-0.12	-0.18
10	0.55	0.34	-0.07	12.62	0.12	51.16	-0.16	-0.11
				Wage Deciles				
1	0.74	5.84	0.20	10.25	0.10	71.04	0.21	0.21
2	0.74	6.20	0.06	13.52	0.16	71.97	0.05	0.05
3	0.70	6.39	0.02	10.91	0.12	72.98	0.00	0.00
4	0.69	6.55	-0.06	13.60	0.16	70.23	-0.10	-0.10
5	0.66	6.71	-0.09	13.23	0.16	70.86	-0.14	-0.14
6	0.65	6.86	-0.12	12.70	0.14	64.65	-0.18	-0.18
7	0.60	7.03	-0.16	13.78	0.15	60.74	-0.23	-0.23
8	0.58	7.22	-0.19	14.16	0.15	60.94	-0.26	-0.26
9	0.59	7.46	-0.23	12.51	0.12	54.84	-0.30	-0.30
10	0.59	7.89	-0.32	13.97	0.11	46.59	-0.38	-0.38

This Table contains means by (Part A) PCT, (Part B) SKL, and (Part C) real wage decile of (1) the fraction of displaced workers changing occupation, (2) the mean rank in the job, (3) the mean change in the real wage between the lost and current job, (4) weeks unemployed post-displacement, (5) the fraction exhausting their UI benefits, and, for occupation switchers, (6) mean values of $ANGL$, (7) the mean change in job rank (PCT, SKL or real wage,) and (8) the mean change in the real wage. The information in column (7) of Part C is redundant but is presented to preserve symmetry.

Table 2: Means of Career Transition Variables by Rank Increase or Rank Decrease

	A. *PCT* Deciles					
	Wks Unem		Exh. UI		ANGL	
Decile	$\Delta R > 0$	$\Delta R < 0$	$\Delta R > 0$	$\Delta R < 0$	$\Delta R > 0$	$\Delta R < 0$
	(1)	(2)	(3)	(4)	(5)	(6)
1	11.35	15.25	0.11	0.00	72.13	55.92
2	12.36	14.12	0.11	0.11	74.32	52.77
3	11.52	9.04	0.12	0.11	78.71	70.37
4	13.33	13.93	0.13	0.13	69.17	73.68
5	15.53	14.78	0.16	0.16	69.22	74.35
6	12.61	15.89	0.15	0.20	64.51	73.83
7	14.18	14.91	0.14	0.17	62.85	71.93
8	13.43	14.79	0.14	0.17	46.86	65.14
9	12.90	14.44	0.12	0.17	49.19	64.78
10	12.21	14.51	0.08	0.18	69.76	66.59
	B. *SKL* Deciles					
1	13.54	18.59	0.16	0.23	69.28	44.37
2	14.33	15.16	0.16	0.18	71.89	51.27
3	14.48	12.84	0.12	0.18	75.60	57.29
4	12.39	13.65	0.15	0.14	76.95	70.52
5	13.87	13.43	0.14	0.18	74.55	68.68
6	13.69	14.72	0.16	0.16	70.40	72.79
7	13.77	12.64	0.12	0.14	60.68	77.25
8	12.26	14.19	0.12	0.16	38.97	75.65
9	11.54	15.33	0.10	0.16	37.14	66.68
10	11.51	14.97	0.08	0.16	32.23	54.91
	C. Wage Deciles					
1	9.57	11.73	0.08	0.13	71.77	69.37
2	12.39	14.80	0.14	0.19	71.03	73.02
3	9.31	12.56	0.09	0.16	71.58	74.28
4	10.33	16.06	0.12	0.19	66.40	72.68
5	9.87	15.42	0.10	0.20	66.22	73.22
6	9.70	14.87	0.10	0.16	62.25	66.10
7	10.09	15.64	0.10	0.18	54.62	63.17
8	11.06	15.84	0.11	0.17	52.60	64.62
9	9.34	14.19	0.07	0.15	47.74	57.88
10	10.64	14.98	0.09	0.12	39.08	48.50

This Table contains means by (Part A) PCT, (Part B) SKL, and (Part C) real wage decile of weeks unemployed (1,2), the fraction exhausting their UI benefits (3,4) and $ANGL$ (5,6) for those experiencing rising ($\Delta R > 0$) and declining ($\Delta R < 0$) job rank, where $R = PCT,\ SKL$, or the real wage. We see generally higher mean values of $ANGL$ at lower ranks for rank increases (col. 5) than rank decreases (col. 6), which is consistent with career trajectory upgrade. We also see higher mean values of $ANGL$ at higher ranks for rank decreases than rank increases, which is consistent with the importance of task specificity.

Table 3: Mean Skill Composition Change by Decile: Actual versus Random Mobility

	PCT			*SKL*			*WAGE*		
Rank	Disp	Cont's	Random	Disp	Cont's	Random	Disp	Comp	Random
1	70.8	71.8	89.1	66.1	65.0	89.9	71.0	65.5	89.1
2	71.5	69.5	87.9	66.0	70.8	90.1	72.0	65.5	90.0
3	75.6	78.2	91.0	69.2	76.5	90.9	73.0	64.8	90.2
4	69.2	69.4	86.8	74.0	73.2	91.0	70.2	64.1	89.1
5	70.9	74.9	88.7	71.9	73.5	90.1	70.9	62.2	88.1
6	65.6	64.7	89.1	71.7	64.2	90.1	64.6	60.6	86.8
7	68.0	63.9	88.2	71.3	59.6	88.3	60.7	58.1	87.1
8	58.1	55.4	87.5	62.7	57.1	86.0	60.9	54.9	84.3
9	59.3	55.6	87.1	58.5	50.7	83.4	54.8	49.3	86.4
10	66.0	62.1	88.4	51.2	51.5	83.1	46.6	42.4	85.5

This Table contains mean values of $ANGL$ in the Displaced, Continuously Employed or Comparison Samples, and under random mobility, by decile rank.

The evidence presented in this Section are consistent with a world in which workers displaced from low-rank jobs make a conscious decision to find higher-rank jobs that make fuller use of their skill sets, taking the form of large changes in skill composition, while workers displaced from high-rank jobs try to find jobs similar to those lost, with larger changes in skill composition leading to larger declines in job rank. The model described in the next Section formalizes these observations.

5 Model Summary

We model the outcomes of displaced workers within a task-specific framework augmented to include the possibility of low-rank workers moving to new, higher-rank jobs that make fuller use of the worker's skill portfolio than did the prior job, which we call career trajectory upgrade. To preserve the flow of the paper, the model proper is relegated to Appendix C and is summarized here. Jobs are characterized by (1) rank, which for us is synonymous with total human capital accumulation, and (2) the composition of two skills, A and B. There are two career stages. Junior workers use a single skill, A, on the job, with output q_{jf} given by

$$q_{jf} = A_j. \tag{4}$$

Senior workers combine the Junior skill and a new, second skill, B, with output given by

$$q_{jf} = \min[A_j, \alpha_f B_j], \quad B_j \geq \bar{B_f} \tag{5}$$

where $\alpha_f > 0$ is specific to firm f. These assumptions imply that skill broadening – acquisition of new skills – is necessary to advance from Junior to Senior stage (Lazear, 2004a; Frederiksen et al., 2016; Frederiksen and Kato, 2017). Both Junior and Senior workers invest in human capital on the job. We assume that Juniors acquire both skills A and B but do not use skill B and are not eligible for promotion until B reaches a firm-specific threshold $\bar{B_f}$. Seniors invest in both skills along a straight-line career path through the origin, acquiring α_f units of skill A for every unit of B, defining the angle θ with respect to the horizontal axis. Skills A and B are transferable across firms, but θ is specific to the firm and deviations from that career path are undesirable.[11]

Changes in skill composition are tied to changes in rank because the rank on job j, ℓ_j is defined to be equal to the Euclidean length of the skill vector,

$$\ell_j = ({A_j}^2 + B_j^2)^{\frac{1}{2}}. \tag{6}$$

When displaced, a Senior worker's rank on a new job is limited to the extent that it uses skills A and B in a proportion different from the lost job. The "scarce" skill can be either A or B but is taken to be B for the purposes of discussion. The situation is different for Juniors, who were using only skill A on the lost job, but were acquiring skill B in preparation for promotion at the old firm. We assume that promotion could have been delayed and that search costs prevented them from leaving their original firm to find a Senior job using their (limited) amount of skill B prior to displacement. The result is that workers who lose lower-rank jobs have the potential to advance their career after being displaced.

The model makes predictions regarding the effects of lost job rank (ℓ) and skill composition change (θ) on the change in rank between the lost and current job ($\Delta\ell$), exposited with the aid of Figures 3 and 4.

1. Changes in skill composition are always deleterious for Senior workers ($\partial\Delta\ell/\partial\theta < 0$). The situation is depicted in Figure 3, in which human capital accumulation and non-transferability are ignored to reduce clutter. Consider a Senior worker who loses a job of rank $\ell_{1,lo}$ that uses skill composition θ_1 (solid line). If her best post-displacement offer uses skill composition θ_2, her rank on the new job, limited by her scarce skill B, declines from $\ell_{1,lo}$ to $\ell_{2,lo}$. If she takes a job entailing larger skill composition change $\theta_3 > \theta_2$, her rank falls by more, to $\ell_{3,lo}$.

2. Senior workers displaced from more highly ranked jobs suffer greater reductions in rank ($\partial\Delta\ell/\partial\ell < 0$). Consult once again Figure 3, and compare two workers displaced from jobs using skill composition θ_1 at ranks $\ell_{1,hi} > \ell_{1,lo}$ (dotted line). It is visually evident that given $\Delta\theta$, the decline in rank is larger for the higher-rank job loser (e.g., $\ell_{2,hi} - \ell_{1,hi} < \ell_{2,lo} - \ell_{1,lo}$).

3. A key new insight is that changes in θ have a more negative impact for Seniors who lose higher rank jobs ($\partial^2\Delta\ell/\partial\ell\ \partial\theta < 0$). In Figure 3, we compare the effects of changes in θ on $\Delta\ell$ for two workers initially employed in jobs using skill composition θ_1, one in a high rank job

($\ell_{1,lo}$) and one in a low rank job ($\ell_{1,hi}$). The effect of an increase in θ on the new job from θ_2 to θ_3 is given by $(\ell_3 - \ell_l) - (\ell_2 - \ell_l) = \ell_3 - \ell_2$. It is visually obvious that $|\ell_{3,hi} - \ell_{2,hi}| > |\ell_{3,lo} - \ell_{2,lo}|$.

4. A second key new insight is that moderate skill composition change can benefit Junior workers ($\partial \Delta\ell / \partial\theta > 0$). Figure 4 depicts a worker separated from a job of rank ℓ_0 that requires A_0 units of skill A. She has acquired B_1 units of skill B, which would have equipped her for promotion to rank ℓ_1 had she not been displaced. Suppose for the moment that human capital is perfectly transferable. If she finds a job along career path $\theta_2 < \theta_1$, she rises in rank, but by less than if she finds a job along path θ_1. Thus, higher θ can increase rank change for Junior workers who find Senior jobs when $\theta_2 < \theta_1$. The case of $\theta_2 > \theta_1$ is more complex.

5. Absent effects of θ on the transferability ϕ of human capital between Junior and Senior jobs, moderate θ_2 interacts positively with lost job rank ($\partial^2 \Delta\ell / \partial\theta_2 \ \partial\ell > 0$) and large θ_2, negatively. Empirically, we find that skill composition change $ANGL$ typically interacts negatively with lost job rank for Juniors, which would require $ANGL$ to be increasing in lost job rank, which finds only modest support in the data (see rank deciles 1 through 3 (PCT. wages) or 4 (SKL) in Table 1). However, the model can generate a negative interaction for moderate skill composition changes if $\partial\phi(\ell_0, \theta_2)/\partial\theta_2 < 0$. Intuitively, a welder might be able to transfer more human capital to a job with some managerial responsibility (where she oversees other welders, corresponding to a moderate θ_2) than to an office job (corresponding to a high θ_2). If, in addition, $\partial^2\phi(\ell_0, \theta_2)/\partial\ell_0\partial\theta_2 < 0$, then the dampening effect would be greater for an experienced welder (high ℓ_0) than a beginner welder (low ℓ_0). Intuitively, the experienced welder might be able to transfer less human capital to the new job because the extra welding human capital is not very useful in managing. This allows the model to generate (a) a positive effect of skill composition change for Juniors that (b) declines in lost job rank. The story is more complex if $\theta_2 > \theta_1$. Skill composition change may not *guarantee* increases in rank for Juniors, but our model shows that it is at least *possible*.

We now turn to the regression analysis.

6 Regression Analysis of Rank Change

The theoretical model predicts that skill composition change reduces rank for workers who lose higher-rank jobs and interacts negatively with rank on the lost job. Skill composition change can increase rank (up to a point) for those who lose lower-rank jobs, and may interact either negatively or positively with lost job rank. These predictions guide our specification.

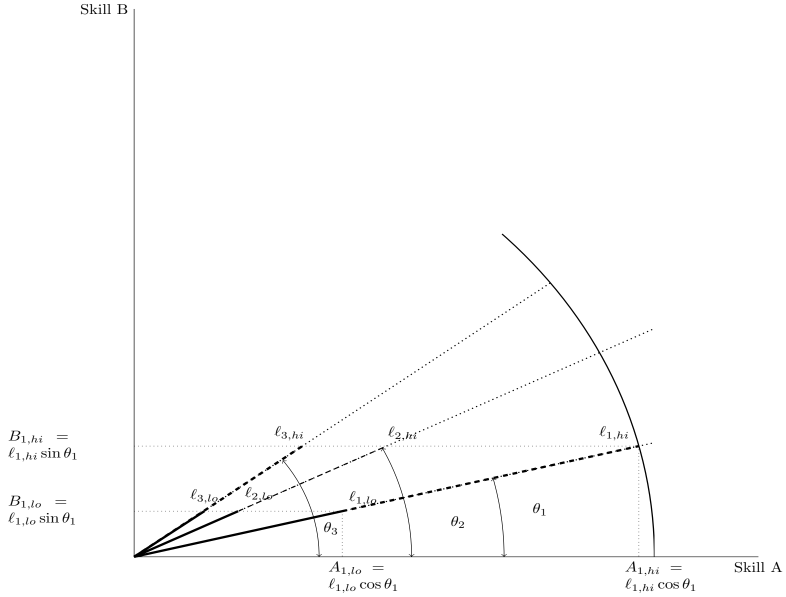

Figure 3: Theoretical Model: Effects of Lost Job Rank for Seniors

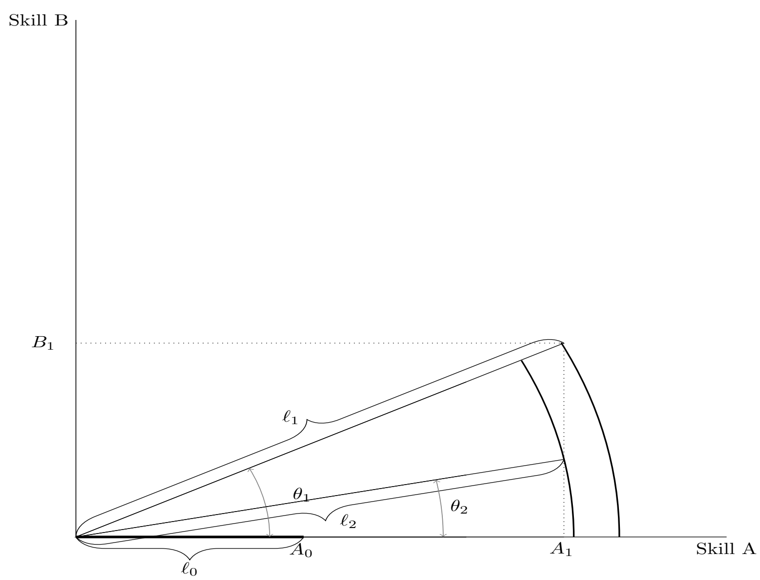

Figure 4: Theoretical Model: Effects of Angular Separation for Juniors

6.1 Specification

We estimate two specifications of the rank change models. Starting with PCT, the parsimonious specification is

$$\begin{aligned}\Delta PCT_{icl} = \beta_P LPCT_{il} + \beta_A ANGL_{icl} + \beta_{PA} LPCT_{il} \times ANGL_{icl} \\ + \beta_S LSKL_{il} + \beta_X X_i + \Delta\epsilon_{icl},\end{aligned} \tag{7}$$

where ΔPCT_{icl} is the change in PCT for an individual i displaced from a job in occupation l and currently employed in occupation c, $LPCT_{il}$ is PCT on the lost job, $ANGL_{icl}$ is as in Equation 3, X_i is a vector of control variables, and $LSKL_{il}$ is SKL on the lost job (see Equation 2). Our key new insights are manifested by the inclusion of the interaction between $ANGL$ and $LSKL$. The partial derivatives of Equation 7 with respect to $LPCT$ and $ANGL$, relegated to Appendix E to reduce clutter, reveal that for the career trajectory upgrade story to be empirically relevant, we must have $\beta_A > 0$, and for the task specificity story to be empirically relevant, we must have $\beta_{PA} < 0$. The coefficient β_P is also expected to be negative.

The error term $\Delta\epsilon_{icl}$ equals the difference between the error terms in the current and lost jobs, $\epsilon_{ic} - \epsilon_{il}$. Although $ANGL_{icl}$ varies at the 3- or 4-digit (depending on sample year) occupation level, $LPCT_{il}$ and $LSKL_{il}$ vary at the 3-digit Integrated Public Use Microdata Series (IPUMS) 1990 occupation level, and so is the unit on which the standard errors are clustered.

The "Junior-Senior Specification" allows the effects $ANGL_{icl}$ and $LPCT_{il}$ to differ between Junior and Senior workers, and is given by

$$\begin{aligned}\Delta PCT_{icl} = I(JR) \times \{\beta_{PJ} LPCT_{il} + \beta_{AJ} ANGL_{icl} + \beta_{PAJ} LPCT_{il} \times ANGL_{icl}\} \\ + I(SR) \times \{\beta_{PS} LPCT_{il} + \beta_{AS} ANGL_{icl} + \beta_{PAS} LPCT_{il} \times ANGL_{icl}\} \\ + \beta_S LSKL_{il} + \beta_X X_i + \Delta\epsilon_{icl}.\end{aligned} \tag{8}$$

$I(JR)$ and $I(SR) \equiv 1 - I(JR)$ are indicators for the career trajectory upgrade Junior and post-career trajectory upgrade Senior stage. We test the joint null hypotheses given by

$$\beta_{PJ} = \beta_{PS}; \;\; \beta_{AJ} = \beta_{AS}; \;\; \beta_{PAJ} = \beta_{PAS}, \tag{9}$$

and take rejection as evidence that scrutiny of the predicted effects based Equation 7 is warranted.

Equations 7 and 8 are estimated for occupation switchers because (1) the model applies only to switchers and (2) $\Delta PCT_{icl} = ANGL_{icl} = 0$ for non-switchers and we wish to avoid picking up a purely mechanical relationship. The controls in X_i align with Farber (2017), and include vectors in age, formal schooling, job tenure, years since displacement, other demographic controls, and dummy variables for survey year. The estimated effects of these controls, summary statistics for which (except the year dummies) are contained in Table 4, are unremarkable and so are not discussed. The interaction between $ANGL_{icl}$ and $LSKL_{il}$ entered with mixed sign and was

Table 4: Summary Statistics, Rank Sample
Occupation Switchers Only

	Displaced		Plant Closure		Cont'sly Employed	
	Mean	SD	Mean	SD	Mean	SD
$LPCT$	59.542	25.895	61.165	25.390	58.579	26.800
$LSKL$	0.007	0.198	-0.002	0.196	0.028	0.207
ΔPCT	-2.776	33.495	-4.111	33.263	1.988	33.446
ΔSKL	-0.013	0.206	-0.019	0.210	0.009	0.212
$ANGL$	66.001	34.175	66.881	34.364	64.687	34.837
× PCT/100	38.161	27.281	39.789	27.988	36.215	26.903
× SKL	-0.375	13.830	-0.612	13.827	0.554	14.173
Tenure 0-1 Year	0.189	0.391	0.147	0.354		
Tenure 1-3 Years	0.318	0.466	0.294	0.456		
Tenure 3-10 Years	0.343	0.475	0.367	0.482		
Tenure 11-20 Years	0.093	0.290	0.119	0.324		
Tenure 20+ Years	0.057	0.232	0.073	0.260		
Displaced 1 Year Ago	0.326	0.469	0.292	0.455		
Displaced 2 Years Ago	0.352	0.477	0.338	0.473		
Displaced 3 Years Ago	0.318	0.466	0.367	0.482		
Displaced Unknown	0.004	0.063	0.004	0.061		
Age 20-24	0.098	0.298	0.091	0.287	0.056	0.230
Age 25-34	0.305	0.460	0.297	0.457	0.232	0.422
Age 35-44	0.277	0.448	0.287	0.452	0.292	0.454
Age 45-54	0.223	0.416	0.224	0.417	0.278	0.448
Age 55-64	0.097	0.296	0.101	0.301	0.142	0.349
Educ: Dropout	0.087	0.282	0.097	0.296	0.060	0.238
Educ: HS Deg	0.320	0.467	0.358	0.479	0.310	0.462
Educ: Assoc Deg	0.108	0.311	0.109	0.312	0.098	0.298
Educ: Some Coll	0.213	0.410	0.215	0.411	0.187	0.390
Educ: Coll Grad	0.271	0.445	0.221	0.415	0.344	0.475
Female	0.373	0.484	0.401	0.490	0.424	0.494
Black	0.105	0.306	0.107	0.310	0.111	0.314
Hispanic	0.131	0.338	0.139	0.346	0.109	0.312
Other race	0.051	0.221	0.053	0.224	0.060	0.238
Observations	11,774		4,400		42,120	

insignificant, and is therefore excluded (see Appendix Table H1).

In the parsimonious specification, $LPCT_{il}$ does "double duty," capturing both the effects of lost job rank (Implications 2 and 2A in Appendix C) and the distinction between career stages. In the Junior-Senior model, we experiment with

$$I(JR) \equiv LPCT \leq k, k = 10, 20, ..., 90,$$

but, focus on the lower half of the PCT distribution, where career trajectory upgrade is concentrated (Setion 4. Because Equation 8 risks "over-fitting" the model, we regard the Junior-Senior estimates primarily as a check on the parsimonious approach.[12]

6.2 IV Estimation

Researchers recognize that skill composition change is a constrained choice and not randomly assigned (Herz, 2019; Cortes and Gallipoli, 2018; Macaluso, 2017; Kosteas, 2019). However, we are not aware of research that attempts to address the potential consequences of endogeneity on the earnings or rank outcomes of displaced workers, discussed in Appendix D. We deal with potential endogeneity by exploiting the fact that occupation-level means of $ANGL$ are good predictors of, and can be used as IVs for individual-level values of $ANGL$ because they break the potential correlation between individual-level skill composition shocks and rank shocks.

Means from the Displaced Worker Sample are likely to be the best predictors, and are (ignoring the "own" observation) potentially valid. However, means from the Comparison Sample are of interest because month-to-month employment transitions are mostly voluntary and entail little (non-identifiable) displacement. Instruments based on Continuously Employed Sample means are of particular interest because they reflect transitions along a career path mutually beneficial to worker and firm. Such predictability is consistent with the notion that their search process produces results that roughly – perhaps only very roughly – mimic the transitions of the continuously employed.

For the parsimonious estimates, the first stage is

$$\begin{bmatrix} ANGL \\ ANGL_{icl} \times LPCT_{il} \end{bmatrix} = \Gamma_X, X'_{il} + \Gamma_A ANGL_l^{CE} + \Gamma_{PA}[ANGL_l \times LPCT_{il}]^{CE} + \Upsilon_{icl}, \tag{10}$$

where CE superscripts indicate occupation-specific means of those variables calculated using the Continuously Employed Sample and where X'_{il} contains all of the remaining variables. In the Junior-Senior estimates, $ANGL$ and its interactions with lost job rank are interacted with $I(JR)$ and $I(SR)$. The model is just identified, but we can test for overidentification by exploiting the existence of additional instruments in the form of means from the Non-Displaced sample. The analysis in Appendix Section D.2 shows that our instruments generally pass this test for validity.

6.3 Parsimonious Estimates

Part A of Table 5 presents the coefficients of interest from Ordinary Least Squares (OLD) and IV estimates of Equation 7 for the Displaced (cols. 1-2), Plant Closure (cols. 3-4), and Continuously Employed Samples (cols. 5-6).[13] The instruments are from the Continuously Employed (cols. 2 and 4) and Displaced (col. 6) Samples. The estimated coefficients are positive on $ANGL$ and negative on $LPCT \times ANGL$, implying positive effects of skill composition change for those who lose lower-rank jobs and negative effects for those who lose higher-rank jobs. These results are therefore consistent with career trajectory upgrade for lower rank job losers and task specificity for higher-rank job losers. The estimated coefficients on $LPCT$ are negative, also consistent with the model (particularly for Seniors). The OLS estimated coefficients in the Plant Closure Sample are of only slightly smaller magnitude than those for the Displaced Sample (cols. 1 and 3). The same is true of the IV relative to the OLS coefficients in the Displaced Sample (cols. 1 and 2). However, the IV estimated coefficients for the Plant Closure Sample (col. 4) are markedly smaller and less precisely estimated than the others, an issue examined in more detail in Section 6.8.

6.4 Predicted Effects from Parsimonious Model

Because $ANGL$ and $LPCT$ interact, the predicted effects are shown graphically. Because the null hypothesis of exogeneity is not rejected at the 5% level (the probability values are 9.5% and 8.0% for Displaced and Plant Closed Samples), we focus on OLS estimates. The predicted effects are seen in the top two graphs of Figure 5, expressed in units of standard deviations of $LPCT$, along with 90 and 95% confidence intervals, for the Displaced (solid circles) and Plant Closure (open triangles) Samples. The predicted effect of $ANGL$ are positive at low $LPCT$, and turn negative around $LPCT = 50$. The confidence bands for the Displaced Sample exclude zero at the lowest and highest ranks, and there is no overlap at the extremes. The predictions for the Plant Closure Sample, while noisier, do not differ significantly from the Displaced Sample. Finally, consistent with the model (especially for Seniors), the predicted effects of $LPCT$ evaluated at mean, high, and low $ANGL$ (mean plus or minus one standard deviation) are negative and become more negative as $ANGL$ increases.

6.5 Predicted Effects from Junior-Senior Model

There being little to be gained by examination of the estimated coefficients in Equation 8, we instead summarize tests for endogeneity and Junior-Senior coefficient equality (Equation 9) in Appendix Table E3. There is little evidence of endogeneity in the ΔPCT models in the relevant range. The null hypothesis of Junior-Senior coefficient equality is rejected in the Displaced Sample at the 4.3% level at a cutoff of $LPCT = 20$, and at the 7% level at cutoffs of 60 and 70. To save space, we present results for a cutoff of 60 in the second row of Figure 5, which look little changed relative to the parsimonious model, and present results for cutoffs of 20, 40, and 60 in Appendix

Table 5: ΔPCT and ΔSKL Regressions, Selected Coefficients

	A. Δ *PCT* Models					
	Displaced		Plant Closure		Continuously Employed	
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
LPCT	-0.5602	-0.6371	-0.6357	-0.8145	-0.4755	-0.6465
	(0.0472)	(0.0818)	(0.0621)	(0.1236)	(0.0437)	(0.0879)
ANGL	0.1901	0.2036	0.1255	0.0473	0.2566	0.1290
	(0.0486)	(0.0763)	(0.0613)	(0.1184)	(0.0395)	(0.0889)
$\times$ *LPCT*/100	-0.4856	-0.3549	-0.3989	-0.1297	-0.5424	-0.2732
	(0.0723)	(0.1168)	(0.0881)	(0.1601)	(0.0629)	(0.1252)
Endog P-Val		.0953		.08033		.09993
Kleibergen-Paap F		110.26		69.07		88.04
	B. Δ*SKL* Models					
	OLS	IV	OLS	IV	OLS	IV
LSKL	0.0062	-0.1814	0.0329	-0.1272	0.0431	-0.3563
	(0.0306)	(0.1267)	(0.0321)	(0.1357)	(0.0304)	(0.0850)
ANGL	-0.0003	0.0003	-0.0002	-0.0001	0.0001	0.0002
	(0.0001)	(0.0004)	(0.0001)	(0.0004)	(0.0001)	(0.0003)
$\times$ *LSKL*	-0.0112	-0.0082	-0.0116	-0.0092	-0.0120	-0.0057
	(0.0004)	(0.0020)	(0.0005)	(0.0021)	(0.0004)	(0.0013)
Tenure	Yes	Yes	Yes	Yes	No	No
Age	Yes	Yes	Yes	Yes	Yes	Yes
Education	Yes	Yes	Yes	Yes	Yes	Yes
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Displ Year Effects	Yes	Yes	Yes	Yes	No	No
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
Endog P-Val		.03036		.4018		.0000151
Kleibergen-Paap F		69.10		26.83		42.34
Observations	11774	11770	4400	4398	42120	41995

Standard errors clustered on IPUMS 1990 occupation. Instruments for the Displaced and Plant Closure Samples are Continuously Employed Sample means and for Comparison Sample, Displaced means. All regressions control for age, education, demographics, and sample year effects; displaced samples control for tenure and displacement year effects.

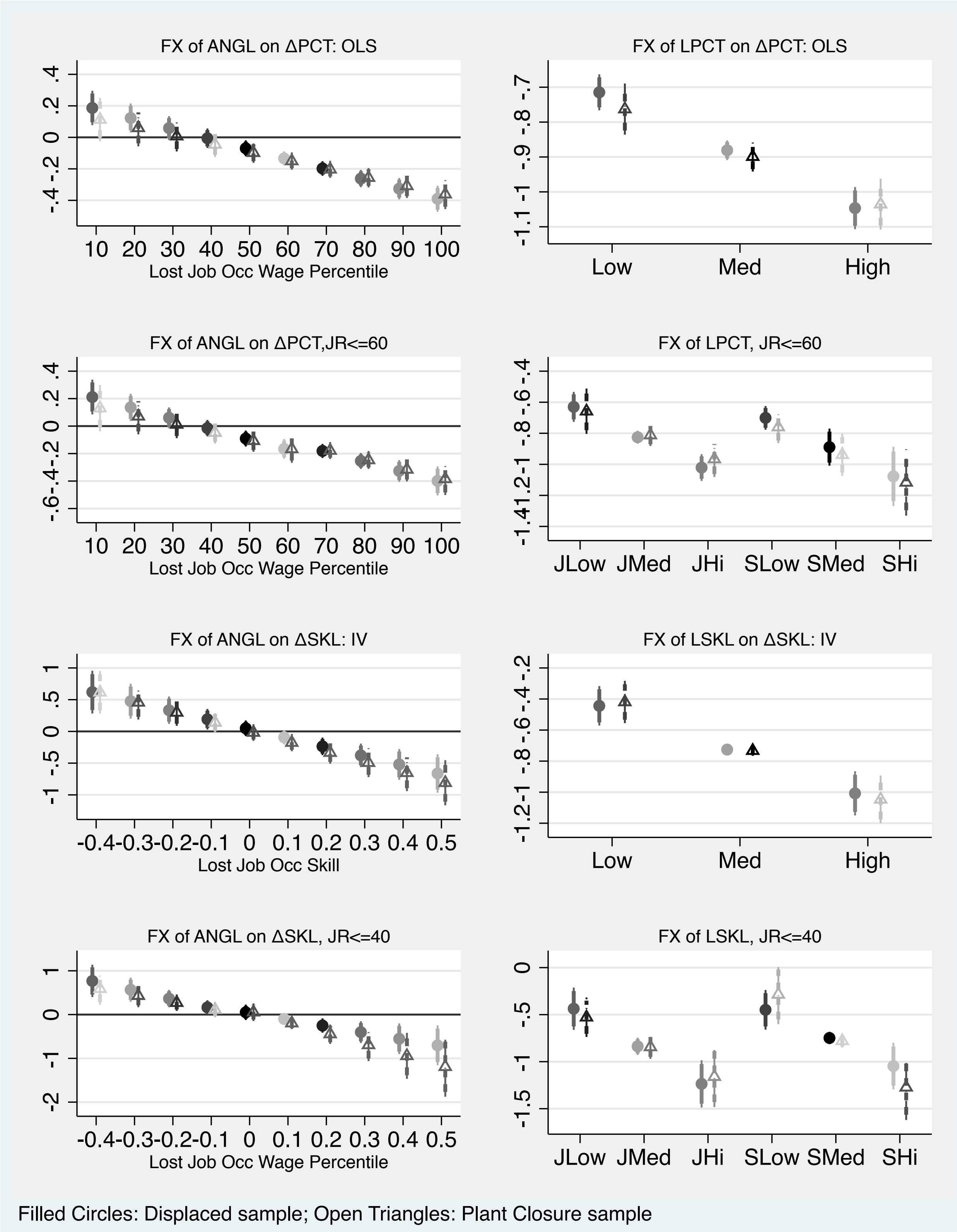

Figure 5: Predicted Effects of Lost Job Rank and $ANGL$ on ΔPCT and ΔSKL

Filled circles = Displaced Sample, open triangles=Plant Closure Sample. Predicted effects and 90/95% confidence intervals of std. dev. increase in $ANGL$ and $LPCT/LSKL$ (Eqn. 7 and its ΔSKL analog). Effects of $LPCT/LSKL$ evaluated at medium (mean), low, and high (minus/plus 1 std. dev.) $ANGL$. Units=std. devs. of $LPCT$ and $LSKL$.

Figure E1. The only significant departure from the parsimonious findings is seen for the effects of $LPCT$ at a cutoff of 20 on Juniors, which rise in $ANGL$; this effect is permitted theoretically (see Equation C19), but is not seen at other cutoffs, which look like those for the parsimonious model. The predicted effects for the Plant Closure Sample are noisier than, but continue to follow the same pattern as those for the Displaced Worker Sample.[14]

6.6 ΔSKL Models

The ΔSKL analogs of Equations 7 and 8, omitted here to reduce clutter, are obtained by interchanging PCT and SKL. Selected coefficients for the parsimonious SKL analog of Equation 7 are contained in Part B of Table 5. It is trickier to interpret the sign pattern because $LSKL$ takes negative as well as positive values (see Table 1).[15] The null hypothesis of exogeneity is now rejected at the 5% level (probability value=0.03) for the Displaced Sample, and we therefore present IV predicted effects. We also present IV predicted effects for the Plant Closure Sample, which are not too different from OLS (probability value = 0.40).

The predicted effects for the parsimonious SKL models are graphed in the third row of Figure 5, and show even clearer signs of career trajectory upgrade at lower ranks and of skill specificity at higher ranks than in the ΔPCT models. Predicted effects from a Junior-Senior model with a Junior cutoff of 40 are seen in the bottom row of Figure 5, for which the null hypothesis of Junior-Senior coefficient equality is rejected at the 6.1% level in the Displaced Sample; predicted effects for cutoffs of 20, 40, and 60 are shown in Appendix Figure E1, which are seen to be reasonably consistent with those from the parsimonious estimates.

6.7 Preferred Estimates

We prefer the parsimonious models because they capture the key features of the data and the picture does not change substantially in the Junior-Senior models. In the Displaced Sample, each standard deviation increase in $ANGL$ implies a 0.12 standard deviation increase in ΔPCT at lower ranks (an average over percentiles 10, 20, and 30), and a 0.26 standard deviation decrease at higher ranks (an average over percentiles 70, 80, and 90); the figures for the Plant Closure Sample are plus 0.06 and minus 0.26. The effects on ΔSKL are plus 0.33 and negative 0.52 in the Displaced Sample and plus 0.29 and minus 0.65 in the Plant Closure Sample.

6.8 Plant Closure Sample: Alternative Instrument Sets

The estimated IV coefficients in the ΔPCT regressions for the Plant Closure Sample (col. 4 of Table 5) are small and statistically imprecise using Continuously Employed Sample means as instruments. To investigate further, we re-estimate the models using, alternatively, instrument sets derived from the Comparison and Non-Plant Closure Samples, the results of which are seen in Table 6. The estimates using Continuously Employed (CE) means are reproduced in columns 1 and

4. The estimated coefficients in the ΔPCT regression using Comparison Sample (CO) instruments (col. 2) are larger and statistically more precise, but are still statistically insignificant at conventional levels. The magnitudes and significance using Non-Plant Closure (NC) instruments (col. 3) are comparable to those for the Displaced Sample. We speculate that the instruments from the Non-Plant Closure Sample do the best job of capturing the opportunity sets of individuals displaced due to plant closure, which may differ considerably from those faced by non-displaced workers. That said, results for ΔSKL (cols. 4-6) are consistent across instrument sets.

6.9 Comparison Sample Results

Forsythe (2017) finds that patterns of occupation change upward and downward are not unique to displaced workers. Consistent with her observations, the predicted effects for the Continuously Employed and Non-Displaced Samples, presented in Appendix Figure E2, exhibit a pattern similar to the one found for displaced workers, with evidence of career trajectory upgrade at lower ranks and task specificity at higher ranks. This is not to say that displacement imposes no costs, but the transitions seen among displaced workers seem roughly to emulate those of workers not displaced.

6.10 Regression Estimates Using Unadjusted Measures of Rank

Appendix G reproduces much of the analysis in Section 4 and Appendix Table G10 contains the key regression coefficients using the unadjusted rank measures. The regression results are, if anything, stronger using the unadjusted measures, and the patterns of predicted effects, seen in Appendix Figure G2, are similar to those using adjusted measures.

7 Wage Change Regressions

We assume in the theoretical model that wages are directly related to rank, which amounts to assuming that workers earn a return on their human capital investment (Assumption 3 in Appendix Section C.2), and the empirical rank measures PCT and SKL are by construction related to wages. However, the evidence of career trajectory upgrade and task specificity estimated in the rank change regressions need not automatically translate into wages. Our wage regressions replace the interaction of $ANGL$ with $LPCT$ in Equation 7 with an interaction in the real wage on the lost job, given by

$$\begin{aligned} \Delta W_{icl} = \beta_0 + \beta_P LPCT_{ic} + \beta_S LSKL_{ic} + \\ \beta_W W_{il} + \beta_A ANGL_{icl} + \beta_{WA} ANGL_{icl} \times W_{il} + \beta_X X_i + \Delta\epsilon_{icl}, \end{aligned} \tag{11}$$

Table 6: ΔPCT and ΔSKL Estimates, Plant Closure Sample
Alternative Instrument Sets

		ΔPCT			ΔSKL	
	(1)	(2)	(3)	(4)	(5)	(6)
	CE	CO	NC	CE	CO	NC
$LPCT$	-0.8145	-0.7778	-0.5521	-0.0000	-0.0000	-0.0001
	(0.1236)	(0.1024)	(0.1350)	(0.0002)	(0.0002)	(0.0002)
$LSKL$	7.9415	7.9782	7.9016	-0.1272	-0.0699	-0.1750
	(2.5418)	(2.5209)	(2.6184)	(0.1357)	(0.1389)	(0.1777)
$ANGL$	0.0473	0.0760	0.3223	-0.0001	-0.0001	-0.0002
	(0.1184)	(0.0992)	(0.1499)	(0.0004)	(0.0004)	(0.0005)
$\times LPCT/100$	-0.1297	-0.1820	-0.4901			
	(0.1601)	(0.1347)	(0.1745)			
$\times LSKL$				-0.0092	-0.0101	-0.0084
				(0.0021)	(0.0022)	(0.0028)
Endog Chi-Sq	5.043	4.634	5.298	1.824	1.065	2.046
Endog P-Val	.08033	.09857	.07074	.4018	.5871	.3595
Kleibergen-Paap F	69	101	39	27	28	18
Observations	4398	4400	4396	4398	4400	4396
R-Square	.4566	.4591	.4511	.4918	.4964	.4897

Estimates of Equation 7 and its ΔSKL analog. Standard errors clustered on IPUMS 1990 occupation. Instrument set appears below column numbers. CE denotes Continuously Employed, CO denotes Comparison Sample, and NC denotes Displaced, Non-Plant Closure Instruments. All regressions control for age, education, demographics, and sample year effects; displaced samples control for tenure and displacement year effects.

where all variables are as before.[16] The specification of Equation 11 is similar to one estimated by Gathmann and Schönberg (2010) using German panel data; we will have more to say about their estimates in Section 7.4.

The main coefficients from the parsimonious model are contained in Table 7 (full results are contained in Appendix Table F1.). Due to the evidence of endogeneity bias in the Displaced Sample (probability value=0.0008), we focus on IV predicted effects, seen in the top rows of Figure 6. Although endogeneity bias is not evident in the Plant Closure estimates, the IV estimates are similar to those obtained in the Displaced Sample, and differ substantially from OLS estimates, which are about one quarter as large. We therefore present IV predicted effects in the body of the paper and show OLS predicted effects in Appendix Figure F1.

The pattern of predicted effects is similar to that of the rank change analysis, with positive effects of $ANGL$ at low wages, consistent with career trajectory upgrade, declining and becoming negative at higher wages. However, task specificity dominates throughout most of the lost job wage distribution, with the evidence of career trajectory upgrade limited to workers displaced from jobs in the first wage decile (see Table 1). Consistent with the rank change estimates, the effects of lost job wage (that is, the real wage) are negative and decline in $ANGL$.

Keeping in mind that the evidence of career trajectory upgrade in Section 4 is limited to the lowest wage deciles, Figure 6 also presents predicted effects predicted using the Junior-Senior specification (Appendix Equation F.1) for Junior percentile wage cutoffs of 10, 20, and 30, diagnostics reported in Appendix Table F2. The pattern of estimated effects is consistent for the Displaced sample, but become noisy, especially for Junior workers, for the Plant Closure Sample at a cutoff of 30. In contrast to the rank change analysis, the predicted effects of lost job wages are more negative for Junior than for Senior workers. Although permissible in the theoretical model, it is also possible that one of the assumptions – the no-leapfrogging assumption – does not hold.[17]

Table 7: Wage Change Regressions, Wage-Interaction Model: OLS and IV Estimates

	Displaced		Plant Closure		Comparison	
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
W	-0.3396	-0.1562	-0.3542	-0.2420	-0.4413	-0.4530
	(0.0226)	(0.0549)	(0.0330)	(0.0972)	(0.0073)	(0.0154)
$ANGL$	0.0107	0.0300	0.0082	0.0199	0.0077	0.0062
	(0.0017)	(0.0056)	(0.0029)	(0.0091)	(0.0007)	(0.0019)
$\times W$	-0.0018	-0.0045	-0.0014	-0.0030	-0.0012	-0.0011
	(0.0003)	(0.0008)	(0.0004)	(0.0013)	(0.0001)	(0.0003)
Endog Chi-Sq		14.23		2.525		3.264
Endog P-Val		.0008117		.2829		.1955
Kleibergen-Paap F		61		36		60
Observations	9589	9586	3521	3519	196829	196288

Table contains selected estimated coefficients for the wage-interaction model (Equation 11). W denotes log real wage on the lost job. Standard errors clustered on IPUMS 1990 occupation are in parentheses. All regressions control for age, education, demographics, and sample year effects; displaced samples control for tenure and displacement year effects.

7.1 Preferred Wage Estimates

We again prefer the parsimonious estimates on the grounds that they adequately capture the main features of the data. Each standard deviation increase in $ANGL$ is predicted to increase wages by about 0.2 log points for those displaced from the lowest-wage jobs (log wages between 5.0 and 5.8) in the Displaced Sample and decrease wages by about 0.17 log points for those displaced from the highest-wage jobs (log wages between 7.4 and 8.2). The effects for the Plant Closure Sample are positive 0.12 and negative 0.13.

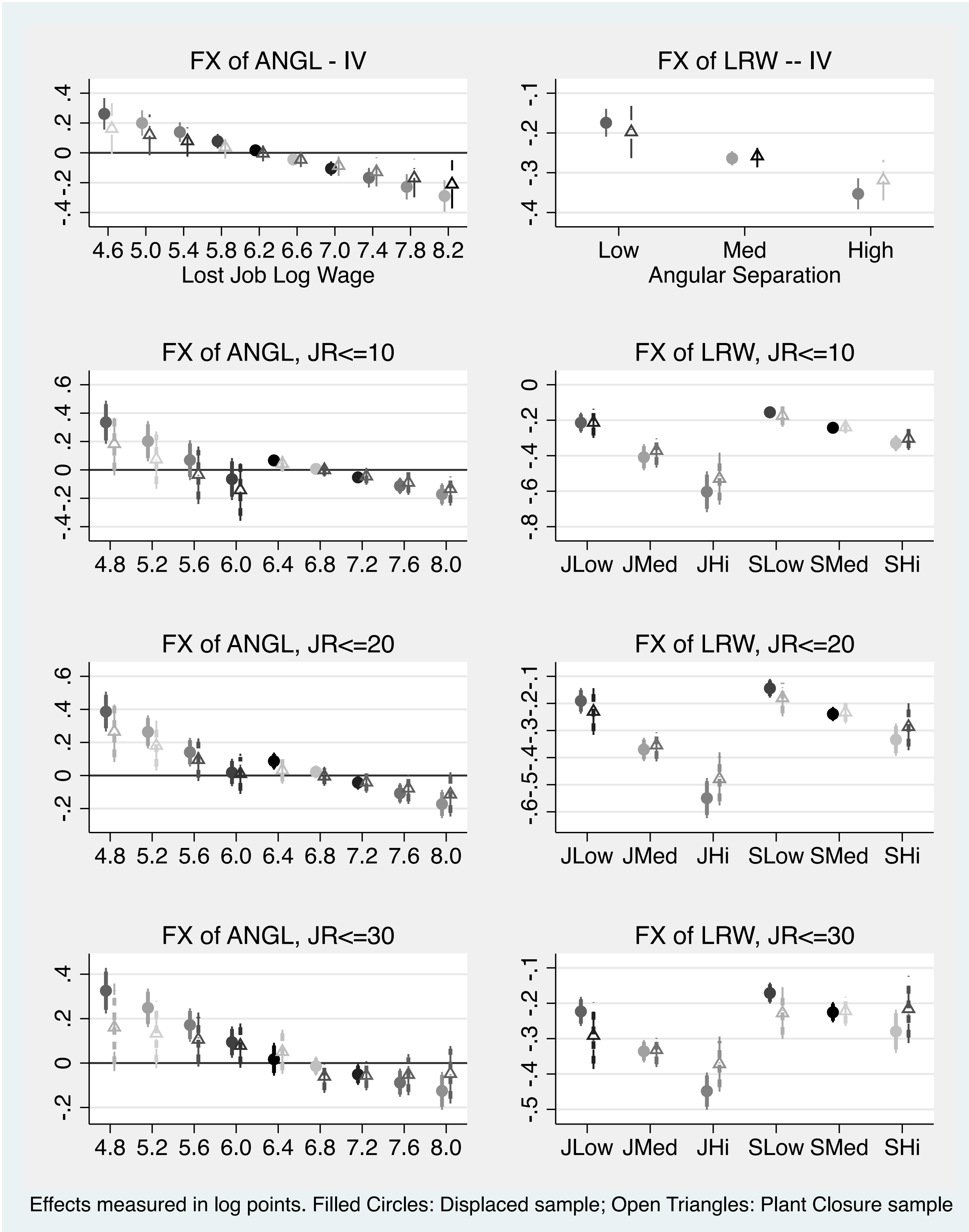

Figure 6: IV Predicted Effects,Wage-Interaction Model

Filled circles = Displaced Sample, open triangles=Plant Closure Sample. IV predicted effects and 90/95% confidence intervals from Equation 11 of a standard deviation increase in *ANGL* and lost job real wage evaluated at medium (mean), low, and high (minus/plus 1 std. dev.) *ANGL*.

7.2 Skill-Broadening Less Evident in Wage Changes than in Skill Changes

That career trajectory upgrade is more apparent in rank changes than in wage changes implies that upward moves in rank translate less readily into wage increases than downward moves translate into wage decreases. This impression is supported by a descriptive exercise in which wage changes are regressed on rank changes where positive and negative changes are permitted to have different effects (Appendix Table H8). It is beyond the scope of this paper to explain this asymmetry.[18] One possibility is that firms are initially uncertain, and only gradually learn about the abilities of those newly hired (Waldman, 1984; Greenwald, 1986; Acemoglu and Pischke, 1998). Another is that displaced workers are moving from high-paying to lower-paying firms, although empirical evidence suggests that such downgrading is a small part of the story (Lachowska et al., 2020). Still another possibility is that displaced workers were well-matched to their jobs. Those who lost low rank jobs and move up gain less than would be apparent from the gain in rank, while those who lost high rank jobs lose more.[19] Future research that follows workers for longer periods of time, perhaps exploiting the panel nature of the CPS as suggested by an anonymous referee, may help determine which, if any, of these stories hold.

7.3 Comparisons with Robinson (2018)

Robinson (2018) finds that changes in skill composition reduce earnings on the new job only when displaced workers experience a decline in job rank ($\Delta SKL < 0$). Our results are consistent with his findings because we find that the effects of skill composition change are more negative for workers who lose higher-rank jobs, who are also more likely to experience a decline in job rank. Although we find that skill composition change benefits lower-rank workers because it enables them to find more highly ranked jobs, the fact that such career trajectory upgrade translates less readily into wages seems broadly consistent with his findings.

7.4 Comparisons with Gathmann and Schönberg (2010)

Equation 11 is similar to one estimated by Gathmann and Schönberg (2010) using German panel data and reported in their Table 6 (23). They, too, estimated positive coefficients on skill composition change (Distance of Move) and negative coefficients on the interaction between skill composition change and wage on the last job. However, they did not dwell on this result, their primary interest being measuring and estimating the effects of occupational and task tenure on earnings. When they add past occupational tenure to the model in their Table 7 (24), it enters positively, consistent with their hypothesis that skills are partially transferable across occupations, and the estimated coefficients on Distance of Move change sign from positive to negative. Further comparisons are difficult because this specification drops wage on the last job and its interaction with Distance of Move. However, it is reassuring that we obtain similar results when we estimate a similar specification.

8 Conclusion

Research has refined the explanation for earnings losses incurred by displaced workers, from lost firm-specific human capital, to occupation-specific human capital, to partial transferability of human capital across occupations, (Poletaev and Robinson, 2008), to skill composition change mattering only when job rank declines (Robinson, 2018). Our paper formalizes these observations and makes new predictions within a task-specific human capital framework (Lazear, 2009), augmented to include career trajectory upgrade (Gibbons and Waldman, 2004; Frederiksen et al., 2016; Frederiksen and Kato, 2017). This framework shows how workers displaced from lower-rank jobs can benefit by changes in skill composition, and explains why workers displaced from more highly ranked jobs tend to lose the most from such changes.

Our evidence is consistent with the augmented task-specific approach. Descriptive analysis shows that displaced occupation switchers who lose lower-ranked jobs tend to exhibit greater changes in skill composition and move up in rank, consistent with career trajectory upgrade, and those who lose higher-ranked jobs tend to exhibit smaller changes in skill composition and move down in rank, consistent with the importance of task specificity. Regression analysis reinforces the notion that skill composition change benefits workers displaced from low-rank jobs and hurts workers displaced from high-rank jobs. We find, too, that skill composition changes affect earnings but, not unlike Robinson (2018), there is evidence of asymmetry: increases in job rank seem to translate less readily into earnings than decreases. More research is needed to determine whether this is due to information problems, match quality, firm quality, or whether the explanation lies elsewhere.

Notes

[1]The Non-Displaced Sample is limited to those ever asked the questions on displacement, and report not having been displaced. A worker who reports not being displaced in the 2nd rotation can be retained for (at least) rotations 1 and 2, and a worker who reports not being displaced in the 8th rotation can be retained for all rotations. By construction, the Non-Displaced sample is smaller and statistics calculated from it are noisier. The main purpose of the Non-Displaced Sample is for tests of over-identification (see Section D.2).

[2]We are grateful to Christopher Robinson (Robinson, 2018) for supplying us with the DOT data by 3-digit 1990-era Census occupation and gender, along with detailed instructions for matching them to both 1990s-era 3-digit, and 2000- and 2010-era 4-digit Census occupation codes. We refer the reader to his paper for additional details. We also make use of a 1980-1990 occupational crosswalk produced by Hirsch.

[3]The characteristics include 11 aptitudes (e.g., intelligence, spatial); 7 skill measures (e.g., general educational development, specific vocational preparation, human interaction, data); 20 activity indicators (e.g., strength, vision); and 11 temperament indicators (e.g., take/follow direction, repetitiveness of the job, stress). The largest factor loads most heavily on reasoning, intelligence, and math skills. Three of the factors load heavily on physical tasks: kneeling, crouching and climbing (second largest), motor skills and finger dexterity (third largest), and vision, acuity, and coordination (fifth largest). The fourth largest factor loads most heavily on talking, hearing, and people skills.

[4]We use the IPUMS 1990 occupation codes in order to avoid estimation of separate rank distributions for 1990 and 2000-era Census occupations, which switched from 3 to 4 digits. The estimated IPUMS 1990 occupation effects are then matched back to the individual-level data, and means calculated as needed by 3 or 4-digit Census occupation code. Because a handful of Census occupation codes match up to more than one IPUMS 1990 occupation code, we expanded the set of IPUMS 1990 occupation codes to make the job rank measures between the displaced and non-displaced samples as similar as possible.

[5]Gathmann and Schönberg (2010) measured skill composition change as 1- $\cos\theta$, which is satisfactory when $S_{jn} \geq 0$, but is not appropriate here because the S_{jn} are factor scores centered on zero.

[6] For the reader interested in testing statistical significance of differences across deciles, standard errors are contained in Appendix Tables A10 and A11. A rough approximation for the standard error of the difference is 1.5 times the larger standard error (since s.e(x_2-x_1) = sqrt($s_2^2 + s_1^2$) <= sqrt ($2s_2^2$) < 1.5s_2, where s_1 and s_2 are the standard errors of x_1 and x_2 and $s_2 \geq s_1$).

[7] The underlying data are contained in Appendix Table A6.

[8] Another possibility is measurement error. However, Farber (2017), who noticed that wages for some displaced workers increase between the lost and new job, ruled out the possibility that measurement error alone explains the wage increases. Why did these workers not leave their lost job voluntarily? He suggests that (1) the new job may not be better than the old job despite offering higher earnings and (2) search is costly. Workers, too, may be risk-averse and hence unwilling to change jobs voluntarily.

[9] A table of correlations is contained in Appendix Table A7. We do not dispute Robinson (2018) that there are significant differences in the magnitudes of skill composition change between displaced and non-displaced workers. Rather, we choose to focus on the correlation. The importance of downward mobility in normal career transitions reinforces findings using administrative data from Denmark (Frederiksen et al., 2016; Groes et al., 2014).

[10] For example, according to Lazear (2009), displaced workers whose skills are traded in thicker markets are more likely to find new jobs closely related to their old one, and thus not experience a large decline in productivity, a proposition that is supported empirically (Macaluso, 2017; Herz, 2019; Kosteas, 2019).

[11] In contrast to Frederiksen et al. (2016) and Frederiksen and Kato (2017), there is no skill-broadening in our model for Senior workers. We therefore use the term “career trajectory upgrade” to refer to moves that make fuller use of the worker’s existing skill portfolio. Empirically speaking, some changes in skill composition for Senior workers could reflect career trajectory upgrade. However this implies that earnings losses should be short-run, whereas research finds such losses to be persistent (Lachowska et al., 2020; Jacobson et al., 1993; Davis and von Wachter, 2011), indicating

that the effects of lost match-specific capital dominate.

[12]We also estimated a version of Equation 7 with quadratics in $LPCT$, which avoids the issue of defining $I(JR$, but it was found to be too restrictive.

[13] Full regression results are presented in Appendix Tables E1 and E2.

[14] The IV predicted effects for a cutoff of 40, not shown to save space, yield a positive effect of $ANGL$ for Juniors that *rises* in $LPCT$, a possibility in our model. However, the RMSE is relatively high, and the endogeneity probability value of 6.3% not only exceeds the conventional 5% level, but is the only close call between cutoffs of 10 and 80, a reminder that even a true null is occasionally rejected.

[15]The effect of $ANGL$ is $\hat{\beta}_A + \hat{\beta}_{AS} LSKL$, which can be positive for workers with low (that is, negative values of) $LSKL$ even if both coefficients are negative.

[16] We consider in Appendix I a rank-interaction specification in which $ANGL$ is interacted with the rank measures $LPCT$ and $LSKL$. Those results display less evidence of career trajectory upgrade among Juniors, but are otherwise not dissimilar. We choose to focus on the wage-interaction specification on the grounds that the lost job wage does a superior job of capturing lost job "rank" in the wage analysis.

[17] Compare Equations C.11 and C.18 (C.26) when $\theta_2 < (>)\ \theta_1$. One possibility is that θ_2 rises sufficiently with rank to switch the inequality, not entirely implausible (see rank deciles 1 through 3 (PCT. wages) or 4 (SKL) in Table 1.). Alternatively, Equation C.26 could be more negative than Equation C.11 when $\theta_2 > \theta_1$; however, although $\tan\theta_1 > \sin\theta_1$, the effects of lost job rank on human capital accumulation and transferability are more negative for Seniors. If $\theta_2 < \theta_1$, one may need to reconsider the no-leap-frogging assumption (Equation C.7), which ensures that workers who lose higher-rank jobs have higher potential rank on the new job. For example, an experienced welder may have acquired less – or suffered more deterioration of – skill B than an inexperienced welder. Justifying such a modification likely requires detailed analysis of specific skills, which we leave for future research.

[18] Kulkarni and Hirsch (2020) find a similar asymmetry in their study of the union wage premium using Displaced Worker Surveys: workers who move from a non-unionized to a unionized job gain less of a premium than workers moving from a unionized to a non-unionized job lose.

[19] Let ℓ_i be the rank of the lost job, $i \in L, H$. Introduce match quality $\mu > 0$, let productivity be $\ell_i + \mu$ on the lost job, let rank change be $\pm\Delta$, and assume $\mu = 0$ on the new job. The change in productivity is $\Delta - \mu$ for the low rank worker and $-\Delta - \mu$ for the high rank worker. I thank Michael Waldman for this suggestion.

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A Data Overview

This Appendix contains tables and discussion that supplement Section 4. It is purely complementary and so does not repeat the analysis in the main paper. We focus here on the adjusted rank measures; analysis of the unadjusted measures is contained in Appendix G.

A.1 Skill Composition Change

Table A1 lists the 20 (3-digit IPUMS 1990) occupations manifesting the most and least degrees of skill composition change between the lost and current job for occupation switchers in the Displaced Sample.[1] Occupations with the largest values of $ANGL$ include computer operators (100 degrees), production supervisors (96 degrees), kindergarten teachers (94), guards and watchmen (90), and pharmacists (88). Occupations with the smallest changes in skill composition include chief executive officers and public administrators (29), clergy (39), writers and authors (40), and managers of service organizations n.e.c. (40).

A.2 Rank

Tables A2 and A3 list 20 highest and lowest rank (3-digit IPUMS 1990) occupations as measured by Equations 1 and 2.[2] Neither measure is perfect. The top 20 PCT occupations include CEOs, managers, and financial professionals; writers and teachers n.e.c. are in the bottom 20 along with farm workers, housekeepers, and gardeners. The top 20 SKL occupations include architects, writers, and mechanical engineers, all of which rank more highly than pharmacists and financial managers, and chief executive officers (not on the list; they rank 26^{th}).[3] The correlation between the two measures, seen in Table A8, is *negative*, equal to -0.14 across 710 3- and 4-digit occupations, suggesting that they capture empirically distinct job characteristics. It can also be seen in Table A8 that the correlation between the *unadjusted* measures, tabulated in Appendix Tables G1 and G2, is a much higher 0.68. Also evident is a negative relationship between lost job rank and the change in rank between the lost and current job.

A.3 Life Cycle Pattern of Skill Accumulation

Although both PCT and SKL have their peculiarities as a measure of rank, both are by construction positively related to wages. Their plausibility is enhanced by the fact that they display life-cycle patterns consistent with what theory tells us about the accumulation of human capital. In the spirit of Yamaguchi (2012), we estimate descriptive regressions, seen in Table A4. It can be seen that both measures are (1) positively related to the level of schooling; (2) increase at a decreasing rate with age; and (3) increase at a decreasing rate with job tenure (Displaced and Plant Closure Samples). Descriptive regressions for the unadjusted measures appear in Table G3.

A.4 Job Composition Change and Career Transitions: A Detailed View

Section 4 shows that conditional on switching occupation, workers displaced from lower-rank occupations jobs tend to exhibit (1) higher values of $ANGL$ and (2) new job ranks higher than the lost job, consistent with skill-broadening. The opposite is true of workers displaced from higher-rank jobs, which is consistent with task specificity. There is also ample evidence of task specificity among workers who lose higher-*wage* jobs, but only modest evidence of career trajectory upgrade for those losing lower-wage jobs.

More can be learned by conditioning mean values of $ANGL$ on the decile of the current as well as lost job. Tables A5 and A6 show the calculations for the Continuously Employed Comparison and Displaced Samples. The rows correspond to lost job deciles and the columns, current job deciles. Means are shown along the diagonals ("decile stayers") and *deviations from the mean* on the off-diagonals. Evidence of career trajectory upgrade is suggested when entries to the right of the diagonal (indicating a rank increase) contain positive values (that is, the mean is higher than for decile stayers). Evidence of task specificity, on the other hand, is suggested when entries to the left of the diagonal (indicating a rank decrease) contain positive values of $ANGL$ (again indicating that the mean is higher than for decile stayers).

Evidence of career trajectory upgrade and task specificity is seen in Part A for PCT deciles, and is even more apparent for SKL deciles in Part B, which could reflect the fact that SKL (unlike PCT) is calculated using the same 5 skill components extracted from DOT characteristics used to calculate $ANGL$ (the S_{jn}; see Section 2.4 and Equations 2 and 3). Examination of the conditional means by wage decile in Part C readily reveals evidence of task specificity. However, the evidence of career trajectory upgrade is less easily perceived, especially for the Continuously Employed Sample in Table A5, but emerges with additional analysis.

The data contained in these Tables are used to produce Figure 2 graphs the conditional means of $ANGL$ in the Continuously Employed, Displaced, and Plant Closure Samples as a function of the absolute difference between deciles, where upward moves in rank decile (marked "+") are distinguished from downward moves and decile stayers (marked "x"). A positively sloped relationship through the "+" markers is evidence consistent with career trajectory upgrade, and a positively sloped relationship through the "x" markers, evidence of task specificity. Positive slopes are readily evident in the graphs for PCT deciles (top) and SKL deciles (middle), and albeit muted, are present for wage deciles (bottom) as well.

Table A1: Angular Separation Top and Bottom 20 Occupations

	ANGL		
Occupation	Displ	Pl Clos	Cont'sly Emp
Computer, peripheral equipment operators	100	102	101
Prod'n sprvsrs or foremen	96	96	98
Kndrgrtn, earlier school tchrs	94	110	80
Guards, watchmen, doorkeepers	90	86	86
Bookkeepers, accounting, auditing clerks	90	94	83
Billing clerks, related financial records processing	89	86	71
Pharmacists	88	89	71
Payroll, timekeeping clerks	87	81	66
Teachers , n.e.c.	87	98	87
Dental laboratory, medical appliance technicians	86	89	86
Health technologists, technicians, n.e.c.	86	87	74
Cashiers	85	78	92
Miners	85	84	66
Secretaries	85	85	86
Architects	84	139	55
Typists	84	65	75
Dispatchers	83	62	78
Sprvsrs of mechanics, repairers	82	84	69
Data entry keyers	82	96	78
Truck, delivery, tractor drivers	82	80	84
Wood lathe, routing, planing machine operators	50	42	53
Ops, systms rsrchrs, anlysts	50	55	46
Buyers, wholesale, retail trade	49	61	57
Molders, casting machine operators	49	62	59
Electrical engineer	48	43	52
Other financial specialists	48	46	45
Heavy equipment, farm equipment mechanics	48	42	49
Advertising, related sales jobs	48	49	55
Drywall installers	47	41	45
Industrial engineers	45	43	55
Human resources, labor relations mgrs	45	54	31
Computer software developers	45	45	48
Ecnmsts, mkt, svy rsrchrs	43	36	41
Financial svs sales occs	41	46	49
Financial mgrs	41	42	39
Mgrs of service organizations, n.e.c.	40	43	41
Writers, authors	40	40	61
Clergy, religious workers	39	46	61
N.e.c. engineers	39	38	46
CEOs and Pub. Admin	29	31	42

Table A2: 20 Highest-and Lowest PCT Occupations
With Changes for Occupation Switchers

Occupation	PCT	ΔPCT Displ	Pl Clos	Cont'sly Emp
CEOs and Pub. Admin	100	-26	-26	-33
Pharmacists	99	-34	-6	-43
Prod'n checkers, inspectors	98	-38	-38	-28
Grinders and kindred	98	-47	-51	-32
Auto body repairers	97	-30	-37	-27
Mgrs, Mrktg, and kindred	97	-33	-37	-26
Butchers, meat cutters	97	-42	-43	-35
Sprvsrs of mechanics, repairers	96	-30	-31	-19
Financial svs sales occs	96	-33	-42	-35
Licensed practical nurses	96	-32	-49	-35
Sprvsrs, proprietors of sales jobs	93	-33	-36	-29
Prod'n sprvsrs or foremen	92	-32	-33	-25
Mgrs, administrators, n.e.c.	90	-22	-23	-18
Aircraft mechanics	90	-31	-27	-25
Dispatchers	89	-36	-42	-35
Printing machine operators, n.e.c.	89	-29	-29	-28
Management analysts	89	-20	-23	-23
Telephone operators	89	-31	-30	-40
Buyers, wholesale, retail trade	89	-24	-31	-26
Painting machine operators	88	-35	-30	-23
Construction laborers	17	27	36	32
Carpenters	16	31	34	39
Clergy, religious workers	15	35	30	32
Helpers, surveyors	15	28	35	31
Editors, reporters	15	46	57	44
Architects	14	33	7	47
Misc food prep workers	14	25	23	26
Guards, watchmen, doorkeepers	13	44	42	49
Gardeners, groundskeepers	11	35	39	37
Housekeepers and kindred	10	31	31	38
Masons, tilers, carpet installers	10	36	51	30
Kndrgrtn, earlier school tchrs	9	20	27	22
Farm workers	8	36	32	33
Primary school teachers	6	13	10	35
Writers, authors	5	45	26	44
Roofers, slaters	5	48	34	57
Teachers , n.e.c.	3	53	53	48
Door-to-door, street sales	2	47	38	53
Taxi cab drivers, chauffeurs	2	29	30	48
Child care workers	2	30	37	38

This table lists the top- and bottom-20 $LPCT$ 3-digit 1990 IPUMS occupations (Equation 1). Also reported are mean changes in PCT between the lost/last and current job.

Table A3: 20 Highest-and Lowest SKL Occupations
With Changes for Occupation Switchers

Occupation	SKL	Displ	Δ SKL Pl Clos	Cont'sly Emp
Architects	0.482	-0.446	-0.718	-0.301
Ops, systms rsrchrs, anlysts	0.439	-0.268	-0.173	-0.233
Lawyers	0.432	-0.334	-0.246	-0.245
Industrial engineers	0.391	-0.192	-0.199	-0.198
Writers, authors	0.382	-0.163	-0.104	-0.246
Civil engineers	0.379	-0.173	-0.330	-0.147
Electrical engineer	0.376	-0.121	-0.102	-0.148
N.e.c. engineers	0.364	-0.069	-0.052	-0.087
Clergy, religious workers	0.360	-0.122	-0.098	-0.169
Mechanical engineers	0.356	-0.142	-0.162	-0.102
Computer software developers	0.309	-0.098	-0.089	-0.108
Accountants, auditors	0.306	-0.184	-0.163	-0.190
Human resources, labor relations mgrs	0.306	-0.203	-0.229	-0.150
Ecnmsts, mkt, svy rsrchrs	0.302	-0.100	0.023	-0.087
Editors, reporters	0.296	-0.175	-0.178	-0.122
Pharmacists	0.294	-0.091	-0.142	-0.110
Insurance underwriters	0.291	-0.167	-0.158	-0.230
Technical writers	0.280	-0.176	-0.197	-0.102
Mgrs in education, related fields	0.276	-0.179	-0.198	-0.120
Financial mgrs	0.269	-0.115	-0.122	-0.119
Child care workers	-0.214	0.083	0.096	0.143
Assemblers of electrical equipment	-0.226	0.080	0.050	0.126
Prod'n checkers, inspectors	-0.227	0.122	0.081	0.176
Grinders and kindred	-0.231	0.067	0.106	0.109
Telephone operators	-0.231	0.253	0.210	0.253
Waiter/waitress	-0.239	0.156	0.159	0.185
Construction laborers	-0.242	0.159	0.170	0.217
Machine operators, n.e.c.	-0.243	0.084	0.078	0.103
Slicing, cutting machine operators	-0.259	0.111	0.126	0.068
Nursing aides, orderlies, attendants	-0.301	0.237	0.228	0.262
Misc food prep workers	-0.303	0.144	0.114	0.164
Vehicle washers, equipment cleaners	-0.309	0.171	0.167	0.199
Textile sewing machine operators	-0.313	0.089	0.080	0.115
Janitors	-0.313	0.221	0.241	0.232
Housekeepers and kindred	-0.323	0.152	0.154	0.173
Freight, stock, materials handlers	-0.337	0.192	0.183	0.183
Laborers outside construction	-0.347	0.210	0.230	0.202
Packers, packagers by hand	-0.358	0.155	0.115	0.156
Packers, fillers, wrappers	-0.383	0.172	0.165	0.147
Stock handlers	-0.389	0.253	0.172	0.311

This table lists the top- and bottom-20 $LSKL$ 3-digit 1990 IPUMS occupations (Equation 2). Also reported are mean changes in SKL between the lost/last and current job.

Table A4: Life Cycle Pattern of $LPCT$ and $LSKL$: Descriptive Regressions

	Dep. Var = $LPCT$			Dep. Var = $LSKL$		
	(1)	(2)	(3)	(4)	(5)	(6)
	Displ	Closure	CE	Displ	Closure	CE
Tenure 1-3 Years	2.3729	3.1124		0.0246	0.0316	
	(0.8419)	(1.1100)		(0.0053)	(0.0066)	
Tenure 3-10 Years	5.3096	6.4575		0.0342	0.0395	
	(1.4077)	(1.5917)		(0.0076)	(0.0092)	
Tenure 11-20 Years	7.8270	7.5865		0.0382	0.0331	
	(1.6920)	(1.9008)		(0.0091)	(0.0112)	
Tenure 20+ Years	6.5485	9.3794		0.0412	0.0377	
	(1.6756)	(1.9867)		(0.0083)	(0.0117)	
Age 20-24	-5.8475	-6.8599	-7.8511	-0.0612	-0.0567	-0.0586
	(1.5357)	(1.9348)	(1.3511)	(0.0104)	(0.0150)	(0.0070)
Age 25-34	-2.8861	-3.3094	-2.4873	-0.0140	-0.0117	-0.0132
	(0.6723)	(0.8508)	(0.5688)	(0.0047)	(0.0068)	(0.0023)
Age 45-54	0.9109	-0.2029	-0.3039	-0.0031	-0.0106	-0.0018
	(0.8076)	(1.0809)	(0.3920)	(0.0040)	(0.0055)	(0.0017)
Age 55-64	-1.0280	-4.0026	-2.0136	-0.0031	-0.0241	-0.0076
	(1.0921)	(1.7814)	(0.7409)	(0.0057)	(0.0082)	(0.0033)
Female	-3.0044	-3.7844	-6.1463	-0.0378	-0.0368	-0.0352
	(2.9604)	(3.1525)	(2.9996)	(0.0145)	(0.0153)	(0.0143)
Black	-2.0123	-1.4099	-5.0674	-0.0560	-0.0592	-0.0657
	(1.2210)	(1.5069)	(1.3334)	(0.0069)	(0.0105)	(0.0084)
Hispanic	-3.4913	-3.5936	-5.3083	-0.0427	-0.0510	-0.0435
	(1.3620)	(1.5127)	(0.9850)	(0.0064)	(0.0078)	(0.0047)
Other race	-0.1724	-2.1076	-1.9316	-0.0042	-0.0082	-0.0263
	(1.2934)	(1.7056)	(1.2845)	(0.0101)	(0.0108)	(0.0074)
Educ: Dropout	-5.6039	-6.2702	-6.0148	-0.0642	-0.0679	-0.0753
	(1.6708)	(2.3520)	(1.7727)	(0.0113)	(0.0138)	(0.0101)
Educ: Assoc Deg	6.0916	5.5208	7.2631	0.0994	0.0981	0.1080
	(2.0815)	(2.0329)	(2.5558)	(0.0125)	(0.0134)	(0.0161)
Educ: Some Coll	3.3733	2.7498	3.2541	0.0637	0.0674	0.0688
	(1.4241)	(1.4613)	(1.3747)	(0.0078)	(0.0097)	(0.0080)
Educ: Coll Grad	8.6602	7.7152	7.1996	0.2152	0.2067	0.2294
	(3.5447)	(3.4953)	(3.7142)	(0.0238)	(0.0246)	(0.0221)
Constant	54.0169	55.8465	61.5335	-0.0571	-0.0615	-0.0226
	(4.6715)	(4.8672)	(4.1715)	(0.0259)	(0.0269)	(0.0233)
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17873	6778	2758722	17873	6778	2758722
R-Square	.05826	.06289	.0455	.2863	.2691	.3117

Note: "CE" denotes the Continuously Employed Sample. This table shows regressions of $LPCT$ and $LSKL$ on a variety of covariates as a way of illustrating the life cycle patterns of both rank measures. Because the samples retain occupation non-switchers, the sample sizes are larger than those in the remainder of the paper. Omitted categories are as follow: Tenure, less than 1 year; Age, 35-44; Eduction, high school degree.

Table A5: Angular Separation and Career Transitions, Continuously Employed Sample
Occupation Switchers Only
Means (Diagonal) and Deviations (Off-Diagonal)

	1	2	3	4	5	6	7	8	9	10
					A. *PCT* Deciles					
1	62.67	-9.94	10.74	12.75	14.98	15.52	17.58	13.33	12.10	20.63
2	10.94	49.55	15.46	20.96	21.53	23.09	25.46	21.53	28.67	35.54
3	7.92	5.17	64.22	8.91	7.38	16.86	15.41	13.73	23.11	32.58
4	8.93	4.59	6.21	66.61	10.45	-2.79	4.46	-0.98	-1.41	5.14
5	5.88	3.51	-0.15	2.35	74.45	-0.79	-8.25	-0.37	0.73	6.80
6	24.70	15.78	31.02	12.44	19.92	49.34	18.35	15.12	16.31	18.26
7	24.13	23.34	22.98	12.96	13.21	13.77	54.02	-3.10	7.07	17.61
8	28.16	27.74	30.58	16.83	26.17	22.80	8.13	43.19	4.25	11.05
9	39.00	41.56	44.19	27.07	39.22	27.26	27.00	12.48	36.22	12.71
10	29.85	34.50	43.69	16.01	27.98	14.48	20.56	3.07	-1.40	50.78
					B. *SKL* Deciles					
1	41.89	9.06	25.84	36.65	49.51	47.87	59.32	66.44	70.69	75.12
2	4.72	49.51	12.89	15.16	31.99	35.17	45.87	49.78	56.28	56.69
3	0.21	-5.13	67.27	-5.64	10.52	21.78	20.73	26.75	36.67	38.37
4	13.77	4.96	-0.41	62.53	7.28	10.07	17.44	23.60	23.93	30.51
5	33.06	25.81	26.10	15.16	53.94	12.96	25.09	23.78	27.56	25.33
6	44.42	36.46	43.77	25.43	23.84	46.49	-2.02	4.19	12.95	10.83
7	68.14	61.75	56.85	47.47	43.24	12.43	33.92	7.21	4.45	8.94
8	78.46	70.50	60.90	52.83	43.59	19.09	8.06	33.68	-2.50	16.53
9	84.92	79.92	75.04	58.05	55.93	32.61	9.79	6.50	26.68	10.69
10	84.83	75.93	72.07	61.73	50.74	29.56	12.87	18.91	9.93	30.11
					C. Wage Deciles					
1	63.79	2.46	3.68	2.85	4.34	5.13	4.06	4.24	-1.33	-9.24
2	0.58	63.93	2.92	4.67	3.41	1.96	1.78	3.67	0.08	-5.71
3	1.68	0.99	64.65	-0.02	0.19	0.35	-1.89	0.57	-1.17	-6.02
4	4.64	2.38	0.13	63.60	0.85	1.48	0.16	-2.17	-5.17	-5.56
5	4.91	4.66	2.90	-0.31	62.49	-0.58	-1.95	-2.12	-8.09	-10.65
6	11.89	5.72	6.82	4.69	4.07	59.04	-0.40	-0.14	-3.40	-6.30
7	12.21	11.12	9.69	8.34	4.27	3.31	56.78	-1.97	-3.12	-8.95
8	13.32	14.38	9.65	10.89	8.01	4.55	3.50	53.26	-3.44	-6.33
9	17.74	18.47	17.63	13.93	12.86	12.36	7.82	7.13	45.63	-2.46
10	14.08	21.89	20.50	19.47	13.75	12.26	10.78	6.98	4.46	38.73

This table shows how $ANGL$ varies in the Comparison Sample conditional on last (rows) and current (columns) job rank decile as measured by PCT (Part A), SKL (Part B), and real wages (Part C). Diagonal entries contain means for decile "stayers" while off-diagonal entries show deviations from the decile-stayer mean. Data in Parts A and B are based on those continuously employed; those in Part C are based on outgoing rotations for which employment continuity cannot be ascertained.

Table A6: Angular Separation and Career Transitions, Displaced Sample
Occupation Switchers Only
Means (Diagonal) and Deviations (Off-Diagonal)

	1	2	3	4	5	6	7	8	9	10
A. *PCT* Deciles										
1	58.95	-10.10	15.39	10.13	22.25	22.60	14.50	20.49	10.90	26.67
2	3.56	53.40	19.21	14.59	22.49	19.52	27.80	25.14	20.94	24.96
3	13.90	5.57	61.23	16.13	12.43	17.86	18.45	17.18	12.31	35.26
4	10.58	11.44	11.99	61.17	14.26	10.15	6.01	2.10	10.73	2.85
5	7.13	-2.41	5.61	0.73	71.16	-5.50	-3.47	-5.98	3.54	4.00
6	27.80	17.51	29.83	15.57	10.85	54.46	7.10	12.04	5.72	10.51
7	23.62	20.65	26.29	11.16	10.94	2.54	59.57	-6.52	7.73	11.20
8	27.87	34.70	26.16	15.48	27.02	17.60	12.65	45.32	0.59	3.45
9	36.92	35.10	37.00	21.66	32.29	20.77	28.02	6.45	42.56	5.49
10	25.49	27.68	30.00	21.44	21.84	5.95	18.40	1.00	-10.47	56.82
B. *SKL* Deciles										
1	43.10	6.95	21.79	36.57	30.02	41.65	41.06	51.76	60.68	78.22
2	2.29	51.83	-1.45	16.61	20.40	27.16	26.85	41.35	50.38	56.59
3	4.11	-0.72	55.89	12.27	3.92	21.59	23.08	34.34	42.16	51.46
4	9.13	-0.23	0.34	68.43	-10.02	2.82	11.55	26.89	26.76	36.04
5	16.30	16.00	9.82	8.15	58.39	7.78	5.75	21.73	30.22	37.17
6	31.72	27.53	20.00	24.69	8.04	55.69	2.16	19.13	21.55	23.16
7	43.95	37.87	27.96	41.84	23.90	12.43	51.72	4.13	15.41	13.30
8	59.73	55.82	54.83	48.83	46.00	43.08	20.05	38.66	-3.35	6.10
9	80.03	74.62	79.75	67.51	62.99	55.17	44.38	11.86	28.73	12.35
10	84.28	92.94	75.61	70.93	62.68	55.02	31.92	17.56	8.31	31.38
C. Wage Deciles										
1	70.16	2.07	0.62	-1.08	7.64	-10.78	9.88	17.69	26.42	4.76
2	5.70	70.26	-1.51	2.88	1.73	0.39	11.14	-17.15	-11.68	1.80
3	5.98	-1.92	73.48	-4.24	-0.45	-5.46	4.12	2.71	-4.46	1.08
4	9.81	5.13	3.57	67.82	-2.17	-8.81	1.85	3.56	10.80	-0.70
5	11.81	11.94	9.32	3.94	66.72	2.80	-4.75	-6.62	-7.18	-16.13
6	17.48	19.12	12.29	12.16	6.44	56.18	5.62	10.85	3.91	-9.44
7	11.77	17.08	12.42	11.39	7.83	11.87	53.44	1.87	7.68	-3.79
8	21.08	30.34	21.43	17.52	21.46	5.53	3.33	52.98	1.23	-1.43
9	25.86	19.39	25.52	19.93	26.60	20.13	12.22	-1.41	46.94	2.96
10	11.82	36.79	36.34	29.88	20.65	30.36	4.52	2.68	1.72	41.82

This table shows how $ANGL$ varies in the Displaced Sample conditional on last (rows) and current (columns) job rank decile as measured by PCT (Part A), SKL (Part B), and the log real wage (Part C). The diagonal entries contain means for "decile stayers" while terms on the off-diagonal show deviations from the decile-stayer mean.

Table A7: Correlations, Angular Separation

	Displaced	Plant Closure	Non Closure	Cont'sly Emp	Comparison
Displaced	1.00				
Plant Closure	0.70	1.00			
Non Closure	0.92	0.35	1.00		
Cont'sly Emp	0.40	0.29	0.39	1.00	
Comparison	0.46	0.34	0.46	0.84	1.00

This table shows correlations of occupation-level mean values of $ANGL$ across the various samples.

Table A8: Correlations, Rank

	PCT	*PCT*, Unadj.	*SKL*	*SKL*, Unadj.	Log Wage
PCT	1.00				
PCT, Unadj.	0.42	1.00			
SKL	-0.14	0.67	1.00		
SKL, Unadj.	-0.18	0.68	0.99	1.00	
Log Wage	0.25	0.69	0.58	0.58	1.00

This table shows correlations of occupation-level mean values of adjusted and unadjusted PCT and SKL in the Displaced Sample.

Table A9: Differences in Search and Skill Composition Change by Lost Job Rank Decile, Displaced Worker Sample

	PCT			*SKL*			*LRW*		
Decile	Weeks Un	Exh UI	*ANGL*	Weeks Un	Exh UI	*ANGL*	Weeks Un	Exh UI	*ANGL*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1	3.90	-0.11	-16.21	5.05	0.07	-24.91	2.17	0.04	-2.39
	(6.61)	(0.02)	(7.15)	(3.00)	(0.04)	(2.60)	(0.87)	(0.02)	(1.91)
2	1.76	0.00	-21.54	0.83	0.02	-20.63	2.40	0.05	1.99
	(2.35)	(0.03)	(2.99)	(1.51)	(0.03)	(1.97)	(1.02)	(0.02)	(1.82)
3	-2.48	-0.02	-8.33	-1.64	0.06	-18.31	3.25	0.07	2.70
	(1.27)	(0.03)	(2.65)	(1.41)	(0.03)	(2.05)	(0.86)	(0.02)	(2.10)
4	0.60	0.01	4.52	1.26	-0.01	-6.44	5.73	0.07	6.29
	(1.63)	(0.03)	(2.16)	(1.31)	(0.02)	(2.01)	(1.00)	(0.02)	(2.20)
5	-0.76	0.00	5.13	-0.44	0.04	-5.87	5.55	0.10	7.00
	(1.37)	(0.02)	(1.86)	(1.10)	(0.02)	(1.79)	(0.94)	(0.02)	(2.31)
6	3.28	0.06	9.32	1.03	0.00	2.39	5.17	0.06	3.85
	(1.05)	(0.02)	(1.68)	(1.17)	(0.02)	(1.94)	(0.98)	(0.02)	(2.49)
7	0.72	0.03	9.08	-1.12	0.02	16.58	5.55	0.07	8.54
	(1.22)	(0.02)	(2.05)	(1.20)	(0.02)	(1.84)	(1.03)	(0.02)	(2.52)
8	1.36	0.02	18.28	1.93	0.03	36.68	4.78	0.06	12.02
	(1.07)	(0.02)	(1.72)	(1.02)	(0.02)	(1.56)	(1.15)	(0.02)	(2.58)
9	1.54	0.05	15.59	3.79	0.06	29.54	4.85	0.08	10.13
	(1.10)	(0.02)	(2.08)	(0.96)	(0.02)	(1.66)	(0.94)	(0.02)	(2.67)
10	2.30	0.10	-3.17	3.46	0.08	22.68	4.34	0.03	9.42
	(2.84)	(0.04)	(6.64)	(1.63)	(0.03)	(1.64)	(1.23)	(0.02)	(2.87)

Differences in means of indicated variable between those declining in rank and rising in rank. Positive values indicate higher mean for those declining in rank. Standard errors in parentheses.

A.4 Standard Errors for Career Transitions

Table A10: Standard Errors of Mean of Key Variables by Lost Job Rank

	A. *PCT* Deciles							
	All Displaced					Occ Switchers		
Decile	Δ Occ	RANK	Δ$WAGE$	Wks Unem	Exh. UI	ANGL	Δ RANK	Δ$WAGE$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1	0.02	0.12	0.03	0.80	0.01	1.62	1.42	0.03
2	0.01	0.07	0.01	0.50	0.01	1.13	0.93	0.02
3	0.01	0.09	0.02	0.46	0.01	1.02	0.89	0.02
4	0.01	0.08	0.02	0.50	0.01	1.05	0.85	0.02
5	0.01	0.07	0.01	0.53	0.01	0.92	0.77	0.01
6	0.01	0.06	0.01	0.38	0.01	0.83	0.64	0.02
7	0.01	0.05	0.01	0.48	0.01	0.96	0.73	0.02
8	0.01	0.05	0.01	0.40	0.01	0.84	0.63	0.01
9	0.01	0.06	0.01	0.35	0.01	0.84	0.60	0.02
10	0.01	0.06	0.01	0.50	0.01	1.05	0.71	0.02
	B. *SKL* Deciles							
1	0.01	0.00	0.02	0.69	0.01	1.03	0.01	0.02
2	0.01	0.00	0.02	0.56	0.01	0.96	0.01	0.02
3	0.01	0.00	0.01	0.53	0.01	1.04	0.01	0.02
4	0.01	0.00	0.01	0.48	0.01	1.02	0.01	0.02
5	0.01	0.00	0.02	0.45	0.01	0.90	0.00	0.02
6	0.01	0.00	0.01	0.47	0.01	0.97	0.01	0.02
7	0.01	0.00	0.01	0.41	0.01	0.97	0.01	0.01
8	0.01	0.00	0.01	0.41	0.01	0.92	0.00	0.01
9	0.01	0.00	0.01	0.36	0.01	0.95	0.00	0.02
10	0.01	0.00	0.01	0.44	0.01	0.97	0.01	0.02
	Wage Deciles							
1	0.01	0.00	0.01	0.38	0.01	0.86	0.01	0.01
2	0.01	0.00	0.01	0.51	0.01	0.91	0.01	0.01
3	0.01	0.00	0.01	0.43	0.01	1.04	0.01	0.01
4	0.01	0.00	0.01	0.52	0.01	1.07	0.01	0.01
5	0.01	0.00	0.01	0.49	0.01	1.08	0.01	0.01
6	0.01	0.00	0.01	0.51	0.01	1.19	0.01	0.01
7	0.01	0.00	0.01	0.56	0.01	1.16	0.01	0.01
8	0.01	0.00	0.01	0.60	0.01	1.26	0.02	0.02
9	0.01	0.00	0.01	0.49	0.01	1.26	0.02	0.02
10	0.01	0.01	0.02	0.55	0.01	1.19	0.02	0.02

See note to Table 1.

Table A11: Standard Error of Means by Rank Decrease and Increase

	A. *PCT* Deciles					
	Wks Unem		Exh. UI		ANGL	
Decile	$\Delta R > 0$	$\Delta R < 0$	$\Delta R > 0$	$\Delta R < 0$	$\Delta R > 0$	$\Delta R < 0$
	(1)	(2)	(3)	(4)	(5)	(6)
1	0.96	6.53	0.02	0.00	1.67	6.95
2	0.73	2.24	0.01	0.03	1.20	2.74
3	0.72	1.05	0.01	0.02	1.08	2.42
4	0.85	1.39	0.01	0.02	1.28	1.73
5	0.90	1.03	0.01	0.02	1.21	1.41
6	0.67	0.81	0.01	0.02	1.18	1.19
7	0.95	0.77	0.02	0.01	1.67	1.18
8	0.85	0.65	0.02	0.01	1.37	1.05
9	0.97	0.52	0.02	0.01	1.86	0.94
10	2.77	0.64	0.04	0.01	6.55	1.06
	B. *SKL* Deciles					
1	0.82	2.89	0.01	0.04	1.08	2.37
2	0.78	1.29	0.01	0.02	1.11	1.63
3	0.82	1.15	0.01	0.02	1.27	1.60
4	0.79	1.04	0.02	0.02	1.44	1.39
5	0.72	0.83	0.01	0.02	1.25	1.28
6	0.80	0.85	0.01	0.01	1.37	1.37
7	1.00	0.66	0.02	0.01	1.35	1.26
8	0.80	0.64	0.01	0.01	1.14	1.07
9	0.73	0.62	0.01	0.01	1.22	1.13
10	1.45	0.74	0.02	0.01	1.23	1.08
	C. Wage Deciles					
1	0.44	0.76	0.01	0.01	1.01	1.62
2	0.67	0.76	0.01	0.01	1.24	1.33
3	0.55	0.66	0.01	0.01	1.54	1.43
4	0.67	0.74	0.01	0.01	1.73	1.35
5	0.65	0.68	0.01	0.01	1.91	1.30
6	0.67	0.72	0.01	0.01	2.00	1.49
7	0.70	0.76	0.01	0.01	2.11	1.38
8	0.83	0.80	0.02	0.01	2.07	1.54
9	0.69	0.64	0.01	0.01	2.20	1.51
10	1.04	0.64	0.02	0.01	2.53	1.34

See note to Table 2.

Table A12: Standard Errors: Angular Separation and Career Transitions, Continuously Employed

	1	2	3	4	5	6	7	8	9	10
					A. *PCT* Deciles					
1	1.62	2.63	3.69	2.64	2.57	2.54	2.94	2.59	2.37	2.79
2	2.82	1.66	2.56	2.10	2.49	2.64	2.70	2.41	2.34	2.75
3	3.96	2.88	2.16	2.80	2.60	2.49	2.86	2.89	2.54	2.53
4	3.26	2.66	2.88	2.18	2.66	2.68	2.70	2.60	2.65	2.56
5	2.58	2.31	2.13	2.20	1.49	2.04	2.18	1.90	1.98	2.16
6	2.71	2.59	1.89	2.07	1.95	1.28	1.97	1.84	1.81	1.77
7	3.37	2.71	2.47	2.05	2.19	2.15	1.45	1.95	2.09	2.54
8	2.19	2.11	2.35	1.82	1.50	1.72	1.61	0.86	1.19	1.69
9	2.19	1.88	1.81	1.84	1.57	1.59	1.76	1.23	0.84	1.44
10	3.11	2.66	2.42	2.27	2.30	2.10	2.62	2.13	1.94	1.58
					B. *SKL* Deciles					
1	0.60	1.13	1.24	1.12	1.48	1.21	1.11	1.99	1.03	1.64
2	1.47	1.11	1.67	1.67	1.80	1.53	1.54	2.09	1.61	1.78
3	2.13	2.25	1.83	2.29	2.40	2.18	2.19	2.33	2.07	2.23
4	1.91	2.11	2.14	1.65	2.32	2.16	2.12	2.28	1.99	1.98
5	2.06	2.18	2.43	2.35	1.56	2.10	2.19	2.35	1.95	1.87
6	1.91	1.95	2.11	2.10	2.04	1.47	1.97	2.14	2.04	1.87
7	1.76	1.84	1.91	1.95	2.12	1.94	1.40	2.10	1.65	1.71
8	2.22	2.32	2.05	2.09	2.32	2.11	2.17	1.40	1.79	1.89
9	1.51	1.72	1.46	1.50	1.47	1.73	1.20	1.43	0.80	1.12
10	2.08	1.60	1.52	1.35	1.14	1.37	1.12	1.28	0.87	0.49
					C. Wage Deciles					
1	0.36	0.62	0.76	0.93	1.07	1.28	1.52	1.70	2.05	2.34
2	0.71	0.40	0.66	0.83	0.96	1.13	1.33	1.55	1.76	2.31
3	0.90	0.73	0.42	0.69	0.86	1.04	1.21	1.33	1.70	1.96
4	1.03	0.89	0.76	0.44	0.71	0.91	1.09	1.20	1.46	1.69
5	1.17	1.06	0.93	0.78	0.45	0.75	0.92	1.07	1.26	1.46
6	1.42	1.24	1.09	0.97	0.80	0.47	0.77	0.96	1.11	1.34
7	1.59	1.35	1.25	1.12	1.00	0.81	0.45	0.74	0.94	1.08
8	1.87	1.59	1.42	1.25	1.15	1.00	0.79	0.42	0.69	0.92
9	2.01	1.99	1.64	1.46	1.32	1.15	1.00	0.73	0.34	0.61
10	2.38	2.47	2.08	1.75	1.54	1.26	1.10	0.91	0.64	0.26

See note to Table A5.

Table A13: Standard Errors: Angular Separation and Career Transitions, Displaced

					A. *PCT* Deciles					
	1	2	3	4	5	6	7	8	9	10
1	4.21	6.18	6.50	7.38	6.10	6.33	7.81	6.46	5.55	6.91
2	5.43	3.35	4.62	4.59	4.72	5.05	4.76	4.45	4.63	6.15
3	6.11	4.63	2.92	4.10	4.57	3.66	3.83	4.42	4.42	4.42
4	6.41	4.58	4.79	3.83	4.94	4.92	4.85	4.93	5.17	5.22
5	4.67	4.08	3.87	3.98	2.77	3.74	3.85	3.69	3.93	5.05
6	4.74	3.67	2.89	3.20	3.39	2.10	3.20	3.44	3.11	3.19
7	5.90	3.87	3.35	3.72	3.71	3.65	2.53	3.56	3.91	4.82
8	5.58	3.44	3.59	3.09	2.81	3.18	3.17	1.76	2.53	3.47
9	4.51	3.76	3.25	3.16	3.17	2.86	3.43	2.76	1.89	2.95
10	6.10	5.14	4.83	4.67	4.94	4.50	5.34	4.90	4.57	3.92
					B. *SKL* Deciles					
1	1.66	2.75	3.01	2.56	3.06	2.77	3.00	2.84	3.14	3.60
2	2.92	2.04	3.20	3.09	3.29	3.68	3.49	3.05	3.82	4.26
3	3.96	3.87	3.07	4.19	3.97	4.38	4.54	4.12	4.43	4.48
4	4.49	4.71	4.60	3.95	4.90	4.81	5.22	4.64	4.69	4.48
5	3.87	4.07	3.89	3.88	2.93	4.10	4.03	3.76	3.62	3.66
6	4.36	4.61	5.07	4.59	4.67	3.73	4.90	4.44	4.44	4.17
7	3.57	3.87	3.93	3.60	3.82	4.10	2.53	3.50	3.50	3.44
8	3.22	3.27	3.30	2.90	3.17	3.30	3.24	2.24	2.84	2.73
9	3.15	2.82	2.96	2.18	2.39	2.52	2.50	2.25	1.40	1.97
10	4.92	5.74	3.71	2.60	2.32	2.32	2.32	2.07	1.64	0.81
					C. Wage Deciles					
1	1.15	2.13	3.18	3.75	4.57	7.22	7.61	12.22	7.41	12.68
2	2.31	1.61	2.69	3.31	4.61	5.62	7.57	6.01	11.74	19.24
3	3.48	3.02	2.20	3.39	4.16	4.81	6.37	8.36	11.85	5.91
4	3.35	3.46	3.40	2.21	3.63	4.74	5.55	7.11	13.77	14.14
5	4.23	3.92	3.49	3.54	2.41	3.70	5.28	6.58	7.12	10.51
6	5.04	4.29	4.43	4.11	4.41	2.63	4.04	5.38	7.00	13.10
7	4.88	4.40	5.04	4.80	3.84	3.87	2.21	3.75	6.24	10.66
8	6.27	6.67	6.17	4.95	4.68	4.76	4.18	2.20	3.53	5.77
9	6.32	8.47	6.08	5.06	6.35	5.31	4.49	3.56	1.94	4.16
10	7.18	6.08	8.11	5.75	7.85	6.18	5.06	3.76	3.27	1.56

See note to Table A6.

B Skill Composition Change: Euclidean Distance versus Angular Separation

Most researchers (Kwon and Milgrom, 2014; Poletaev and Robinson, 2008; Robinson, 2018; Macaluso, 2017; Kosteas, 2019) use Euclidean distance to measure changes in skill composition, equal to

$$DIST_{cl} \equiv \left[\sum_{n=1}^{N} [S_{cn} - S_{ln}]^2 \right]^{1/2} . \tag{B.1}$$

Although $DIST_{cl}$ and $ANGL_{cl}$ appear to be merely slightly different versions of the same thing, Euclidean distance combines the effects of skill composition and rank changes.[1] Suppose as in our model 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 only $A_2 < A_1$ units of skill A, depicted in Figure C5. Angular Separation equals $\theta_2 - \theta_1$, and Euclidean Distance is the rank-weighted difference of the cosines of θ_1 and θ_2,

$$DIST_{cl} = |A_2 - A_1| = |\ell_2 \cos\theta_2 - \ell_l \cos\theta_1|, \tag{B.2}$$

where ℓ_l and ℓ_2 are the lengths of the skill vectors in jobs 1 and 2.[2] Moreover, Euclidean distance will be positive even if worker skills merely expand proportionately, generating a purely mechanical relationship between rank change and Euclidean distance. By contrast, Angular Separation is positive only when the ratio in which skills are used changes.

B.1 Results Using Euclidean Distance Measure of Skill Composition Change

Kosteas (2019) found a negative relationship between the probability of being employed and the average distance between the worker's old occupation and occupations in the local labor market using the Euclidean measure, but not using the Angular Separation measure. This raises the question whether it makes a difference in our case, and so we present a limited set of results using the Euclidean measure.

The key coefficients for the rank and wage regressions are contained in Tables B1 and B2, and predicted effects are seen in Figures B1 and B3. The null hypothesis of exogeneity being decisively rejected in 7 of 8 cases, we focus on the IV estimates. With one exception, the pattern of estimated coefficients is the same as using $ANGL$. The results are particularly weak for adjusted PCT in the Plant Closure Sample, and there is only modest evidence of skill-broadening for the Displaced Sample using that measure. The predicted effects for SKL, wages, and the unadjusted measures look much the same as using $ANGL$.

The question of which measure is preferred may depend on the application. There are good reasons to prefer Angular Separation measure of skill composition change within the task-specific framework. By contrast, the results in Kosteas (2019) indicates that the probability of finding post-displacement employment may be a function of distance in rank as well as in skill composition.

Table B1: ΔPCT and ΔSKL IV Results: Euclidean Distance Measure

	Displaced				Plant Closure			
	(1) Adj *PCT*	(2) Unadj *PCT*	(3) Adj *SKL*	(4) Unadj *SKL*	(5) Adj *PCT*	(6) Unadj *PCT*	(7) Adj *SKL*	(8) Unadj *SKL*
$LPCT$	-0.7981	-0.7142	-0.0001	0.0001	-0.9318	-0.6810	-0.0002	0.0001
	(0.0591)	(0.0725)	(0.0002)	(0.0004)	(0.0900)	(0.0894)	(0.0002)	(0.0004)
$LSKL$	6.4789	8.0065	-0.5177	-0.5079	7.6623	5.6046	-0.4900	-0.4760
	(1.7279)	(2.3152)	(0.0700)	(0.0687)	(2.5877)	(3.3648)	(0.0813)	(0.0834)
$DIST$	1.1109	3.8573	-0.0066	-0.0060	-0.5767	4.7660	-0.0103	-0.0063
	(1.4237)	(1.7237)	(0.0082)	(0.0145)	(1.9359)	(2.1193)	(0.0101)	(0.0165)
$\times LPCT/100$	-4.0433	-5.7046			1.3652	-6.1834		
	(2.4369)	(2.6382)			(3.3583)	(3.2453)		
$\times LSKL$			-0.0901	-0.1064			-0.1069	-0.1295
			(0.0307)	(0.0298)			(0.0357)	(0.0356)
Tenure	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Education	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Displ Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Endog Chi-Sq	32.4	23.49	24.23	22.63	30.56	19.65	16.76	15.97
Endog P-Val	9.20e-08	7.92e-06	5.49e-06	.0000122	2.32e-07	.000054	.0002298	.0003401
Kleibergen-Paap F	231	492	358	234	84	153	105	83
Observations	11770	11770	11770	11770	4398	4398	4398	4398

See Section G for discussion of unadjusted rank measures. Instruments from the Continuously Employed Sample. Standard errors clustered on 1990 occupation are shown in parentheses.

Table B2: Wage Regression Results: Euclidean Distance Measure

	Displaced		Plant Closure		Comparison	
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
W	-0.3254	-0.2583	-0.3333	-0.2700	-0.4478	-0.4519
	(0.0196)	(0.0290)	(0.0296)	(0.0504)	(0.0070)	(0.0102)
$DIST$	0.3683	0.6003	0.3209	0.5446	0.2246	0.2139
	(0.0457)	(0.0824)	(0.0806)	(0.1392)	(0.0214)	(0.0372)
$\times W$	-0.0617	-0.0909	-0.0546	-0.0821	-0.0365	-0.0332
	(0.0069)	(0.0123)	(0.0123)	(0.0205)	(0.0032)	(0.0051)
Endog Chi-Sq		15.05		6.708		3.925
Endog P-Val		.0005399		.03494		.1405
Kleibergen-Paap F		328		187		247
Observations	9589	9586	3521	3519	196829	196288

Displaced and Plant Closure Samples use instruments from the Continuously Employed Sample. Standard errors clustered on 1990 occupation are shown in parentheses.

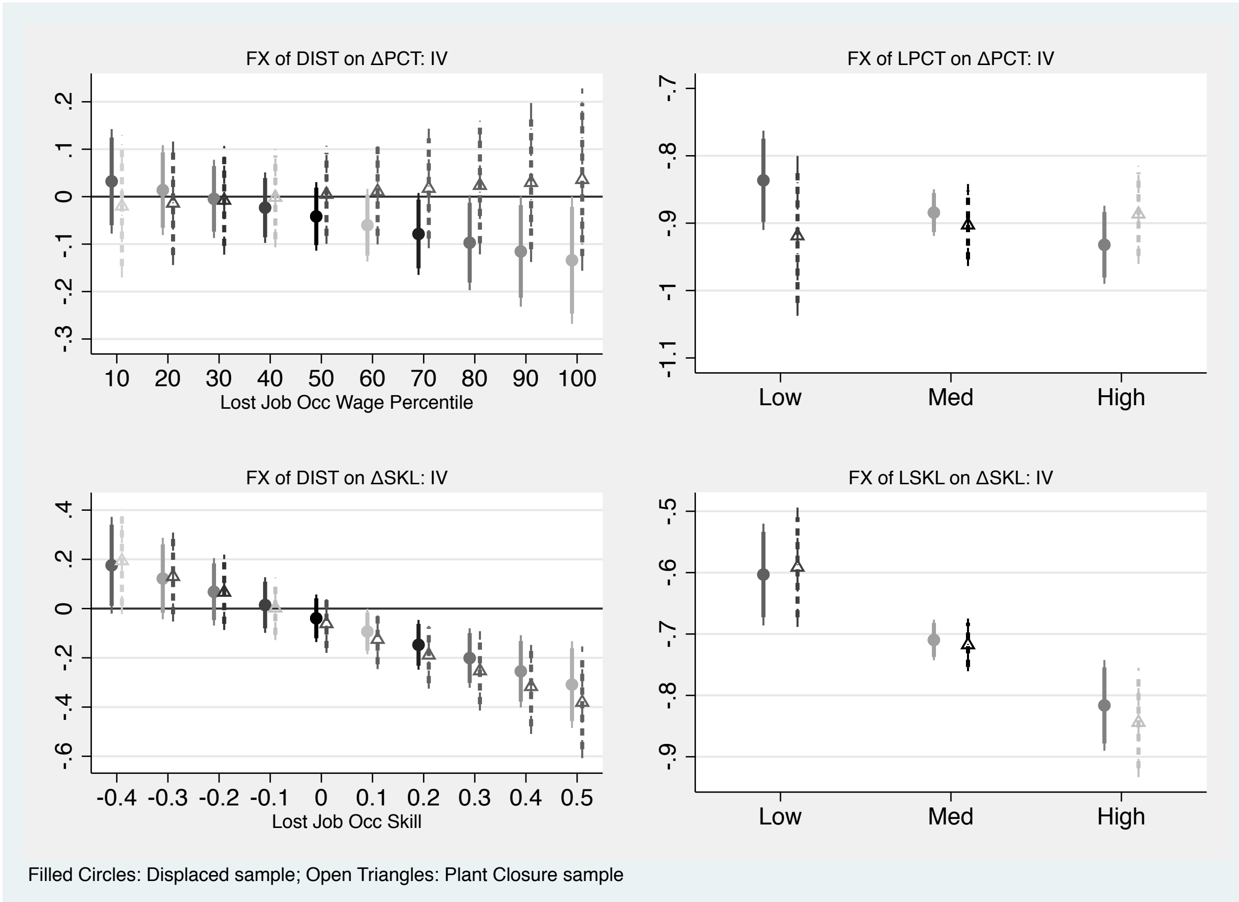

Figure B1: Adjusted Rank IV Predicted Effects: Euclidean Distance Measure

Filled circles = Displaced Sample, open triangles=Plant Closure Sample. IV predicted effects and 90/95% confidence intervals of a standard deviation increase in $DIST$ and lost job rank evaluated at medium (mean), low, and high (minus/plus 1 std. dev.) $DIST$.

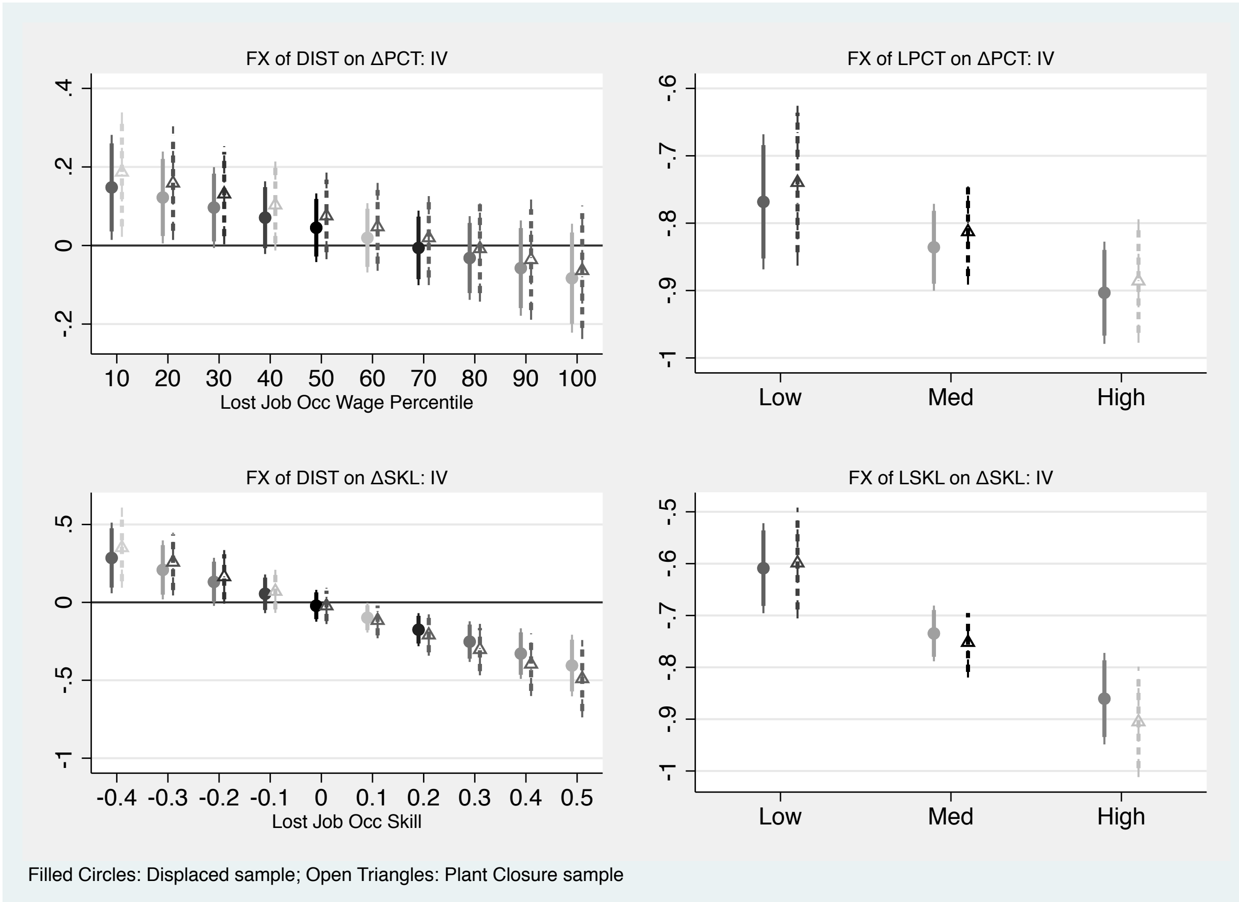

Figure B2: Unadjusted Rank IV Predicted Effects: Euclidean Distance Measure

Filled circles = Displaced Sample, open triangles=Plant Closure Sample. IV predicted effects and 90/95% confidence intervals of a standard deviation increase in $DIST$ and lost job rank evaluated at medium (mean), low, and high (minus/plus 1 std. dev.) $DIST$.

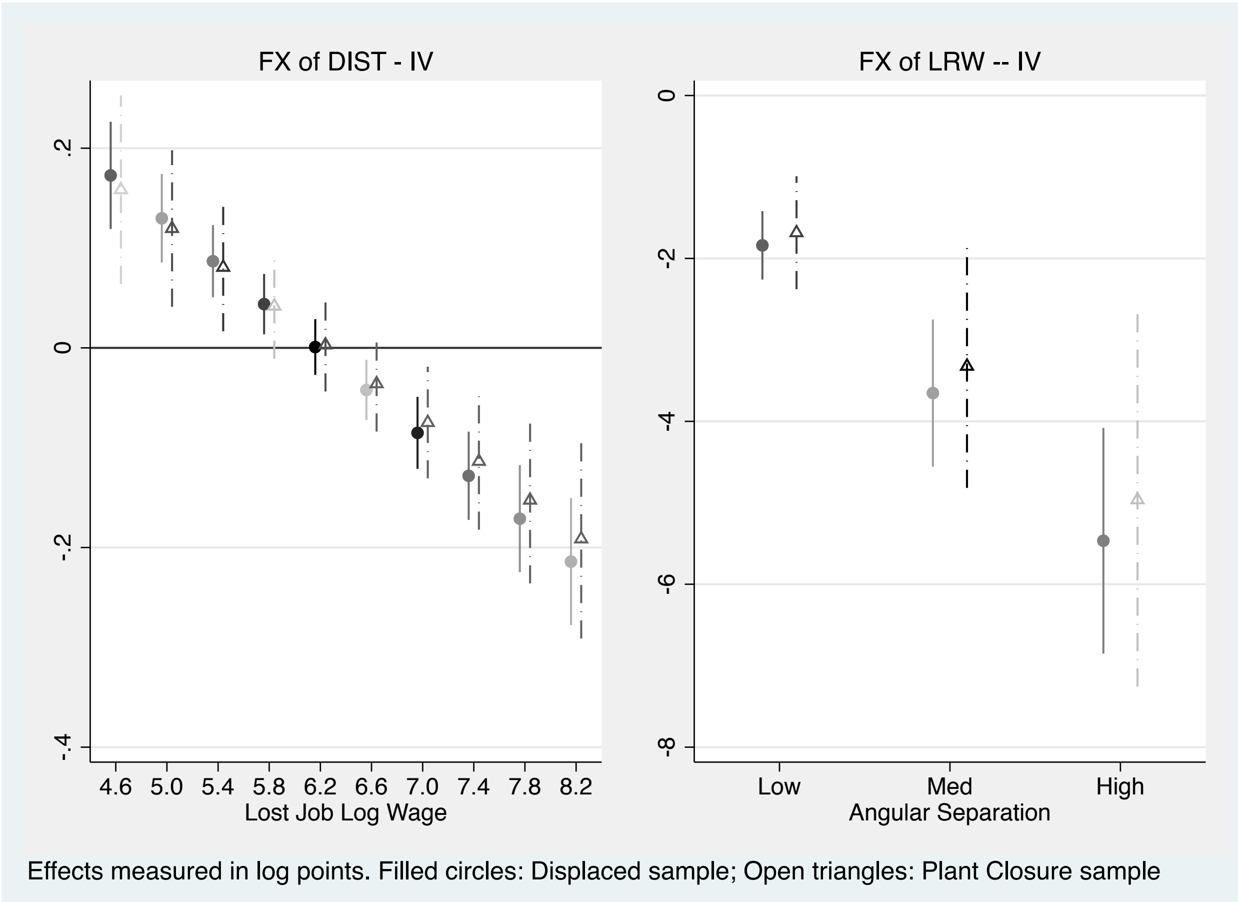

Figure B3: IV Predicted Effects, Wage Change Regressions: Euclidean Distance Measure

Filled circles = Displaced Sample, open triangles=Plant Closure Sample. IV predicted effects and 90/95% confidence intervals of a standard deviation increase in $DIST$ and lost job real wage evaluated at medium (mean), low, and high (minus/plus 1 std. dev.) $DIST$.

Notes

[1]Because $ANGL = 0$ for non-switchers, unconditional means reflect a combination of skill composition change among switchers and the proportion who switch.

[2]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). PCT encapsulates the market value of the skill *bundle*, and contains information beyond that in Equation 2.

[3]Some occupations, such as auto body repairers and butchers and meat cutters, likely rank highly in the PCT distribution due to compensating differences for risk. The lowest wage percentile equals 2 because lower-ranked occupations contain fewer than 20 displaced workers.

[1]Modifications exist. For example, weighting the squared skill difference by the β_n from Equation 2 places more weight on factors with greater impacts on earnings. Robinson (2018) renormalized vector lengths. Finally, the reader may wonder why we did not define job rank as the Euclidean length of the 5-vector $S_1, ..., S_5$. Empirically speaking it falls short. First, DOT characteristics have no natural metric, so empirical changes in its length are not readily interpretable. Second, 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 the progress of a worker's career trajectory.

[2]Duha Altintag suggested an example from our own profession. An assistant professor who is denied tenure may end up taking a job at a lower academic rank (e.g., adjunct professor) which may involve similar tasks on the job, or a job at a consulting firm, which could require a considerably different set of skills. According to our model, the change in rank involved will be greater at the consulting job than in the new academic job.

C A Task-Specific Model of Worker Displacement

We now show how the empirical patterns in Section 4 can be interpreted within a task-specific human capital framework in which what is specific to the firm is not the type of human capital acquired, but the combination in which various skills are used (Gibbons and Waldman, 2004; Lazear, 2009).[1] Jobs are characterized by two components: (1) hierarchical rank, which for us is synonymous with the length of the worker's skill vector, and (2) the composition of two skills, A and B. There are two career stages. Junior workers use just a single skill, A, on the job. Senior workers use a combination of the Junior skill and a new, second skill, B, meaning that career trajectory upgrade is necessary to advance from Junior to Senior stage (Lazear, 2004a; Frederiksen et al., 2016; Frederiksen and Kato, 2017). Senior workers continue to advance by acquiring additional amounts of both skills.[2]

C.1 Brief Summary of Model Implications

Before proceeding, we briefly summarize the implications of the model, thus allowing the reader so inclined to skip to the regression analysis. Recall from Section 4 that workers displaced from lower-rank jobs exhibit relatively high levels of skill composition change and tend to move up in rank, while workers displaced from higher-rank jobs exhibit relatively low levels of skill composition change and tend to move downward in rank. These facts suggest that lower-rank workers acquire human capital on the job that is not fully employed. If a specialized Junior worker who is on the verge of promotion is displaced prior to promotion, she may find a job at higher rank that uses both skills, and greater changes in skill composition can lead to *increases* in job rank. By contrast, changes in skill composition always harm Senior workers, for whom rank on the new job is limited by task specificity – the quantity of their "scarce" skill. The model also shows that lost job rank and changes in skill composition interact within career stage. The direction of this interaction is ambiguous for Junior workers, but for Senior workers, a given change in skill composition leads to larger rank reductions, the higher the rank of the lost job.

C.2 Key Assumptions and Definitions

We follow Lazear (2009) and assume that there are just two skills, A and B, used in all firms, but in proportions specific to the firm. To distinguish between workers lower down and higher up the career ladder, we adapt Lazear's (2004a) distinction between specialists and entrepreneurs to our framework, and identify workers lower down the career ladder as specialists.

Assumption 1 (Junior Workers Specialize) Workers starting their career, called "Juniors," carry out a task that uses only skill A, so that the output produced in a job j at a firm f equals

$$q_{jf} = A_j. \tag{C.1}$$

Assumption 2 (Promotion to Senior Stage Requires Skill Broadening) Promotion to the Senior stage requires a second skill, B. As in Lazear (2004a), A and B are perfect complements, with output after promotion equal to

$$q_{jf} = \min[A_j, \alpha_f B_j], \quad B_j \geq \bar{B_f} \tag{C.2}$$

where $\alpha_f > 0$ indicates the composition of the skills used at firm f, and where the worker cannot advance until B reaches the firm-specific threshold $\bar{B_f}$.

Figure C4 depicts a typical career ladder. A Junior worker carries out a specialized task requiring A_0 units of skill A. The first step on the promotion ladder requires $A_1 = A_0(1 + h_0)$ units of skill A, where h_0 is the rate of human capital investment, discussed in Section C.3, and B_1 units of skill B. The second step on the ladder requires that the worker acquire $A_2 = A_1(1 + h_1)$ units of skill A, and $B_2 = B_1(1 + h_1)$ units of skill B.

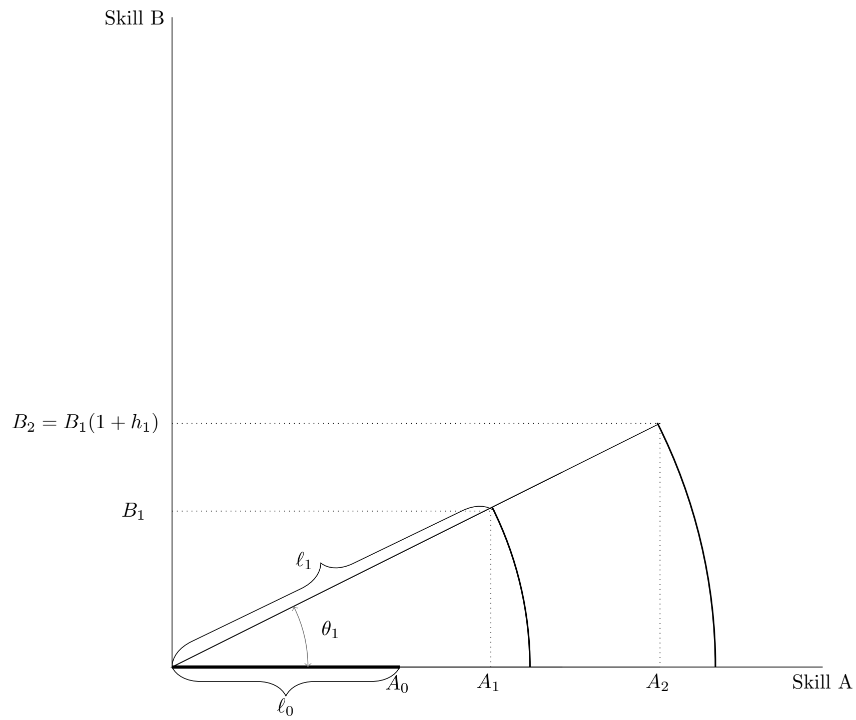

Figure C4: Theoretical Model: Career Path

A worker begins her career at rank ℓ_0 in a specialized job that uses A_0 units of skill A an none of skill B. The worker is in the skill broadening portion of her career, with promotion to rank ℓ_l requiring a combination of skills A and B in amounts $A_1 = A_0(1 + h_0)$ and B_1, where h_0 is the rate of human capital accumulation. At ranks ℓ_l and higher, the worker has moved past the skill broadening portion of her career. Promotion to the next rank (ℓ_2, not shown to reduce clutter) requires $A_2 = A_1(1+h_1)$ units of skill A and $B_2 = B_1(1+h_1)$ units of skill B. The circular arcs show all combinations of skills A and B that are of given rank.

Definition 1 (Job Rank) We identify job rank with the Euclidean length of the skill vector. Consulting Figure C4, rank in the initial job is $\ell_0 = A_0$, but beyond the initial job it equals

$$\ell_j = ({A_j}^2 + B_j^2)^{\frac{1}{2}}. \tag{C.3}$$

All jobs along the circular arc of diameter ℓ_j have identical rank.[3]

Definition 2 (Skill Composition and Skill Composition Change) The skill composition of a job j is defined as the angle made by the skill vector with respect to the horizontal axis, θ_j, and changes in skill composition are measured by Angular Separation $\Delta\theta$. Notice that Angular Separation is distinct from the Euclidean distance between skill vectors, shown in Appendix B to reflect a combination of rank and skill composition change. Skill composition for the Junior worker in Figure C4 is thus $\theta_0 = 0$ (not shown on the Figure to reduce clutter), and, for the worker who advances to the first Senior rank, skill composition is θ_1.

Finally, although the model makes no reference to wages, we analyze wages in the empirical work. We therefore assume the following.

Assumption 3 (Wages are Directly Related to Rank.) Firms combine intermediate outputs of the various jobs j to produce the final output. Absent natural units of measurement, we assume that the unit value to the firm of job j equals p_j, and that the value of the intermediate output is $v_j = p_j q_j = v_j(\ell_j)$. This assumption seems fairly mild, stating merely that workers receive a return on their investment (since rank is increasing in the stocks of skills A and B).[4]

C.3 Human Capital Accumulation

A standard result in theory of human capital investment is that the stock of human capital rises at a decreasing rate with age, which we modify slightly. Equation C.2 implies that $A_j = \alpha_f B_j \quad \forall j$, moving the worker along a straight-line path radiating from the origin, and embodies 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).[5]

Assumption 4 (Stock of Human Capital Rises at a Decreasing Rate in Rank) Human capital investment is non-negative (that is, there is no net depreciation), and the increments to skills A and B are given by $\Delta A_j = \alpha_f \Delta B_j = h(\ell_j)A_j = \alpha_f h(\ell_j)B_j > 0$, with $h(\ell_j) \geq 0$. That human capital investment declines in job rank implies $h'(\ell_j) \leq 0$, and

$$\frac{\partial \Delta B_j}{\partial \ell_j} = \frac{\partial h(\ell_j)B_j}{\partial \ell_j} < 0. \tag{C.4}$$

However, because human capital investment is non-negative, workers displaced from higher rank jobs will always have more human capital than workers displaced from lower rank jobs, so

$$\frac{\partial B_j(1+h(\ell_j))}{\partial B_j} > 0. \tag{C.5}$$

C.4 Delayed Promotion

Farber (2017) suggests that search costs may account for why a substantial fraction of displaced workers experience increases in earnings even after accounting for measurement error, and search costs could help explain why Garg (2016) 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.[6]

Assumption 5 (Promotion May be Delayed) A Senior worker who loses a job j at rank ℓ_j that requires A_j units of skill A and B_j units of skill B has $A_j(1+h(\ell_j))$ and $B_j(1+h(\ell_j))$ units of skills A and B at the time of displacement, and a Junior worker may have acquired sufficient levels of skill B to qualify for promotion.[7] With reference to Figure C4, suppose that we observe a Junior worker displaced from a job $j = 0$, specialized in carrying out a task that requires A_0 units of skill A and does not require skill B at all. It is possible that the worker has actually acquired $A_1 = A_0(1+h_0)$ and B_1 units of skills A and B, which is just sufficient to make the worker eligible for promotion, one that she had not yet received.

C.5 Limitations on Human Capital Transferability

Empirically speaking, the earnings of workers who do not switch occupation can decline, which suggests that the transferability of human capital is limited. There are at least two reasons for limited transferability. First, lateral reentry could interfere with the promotion incentives of existing workers (Lazear and Rosen, 1981; Kwon and Milgrom, 2014). Second, some of the worker's human capital could be truly firm-specific.[8] We therefore build limited transferability into the model.

Assumption 6 (Limited Human Capital Transferability) Let ℓ_p denote the potential rank of the worker when human capital is fully transferable. We assume that the actual rank of a worker displaced from a job $j = 1$ in a new job with potential rank ℓ_p equals $\ell_c = \phi(\ell_1)\ell_p$, $0 < \phi(\ell_1) \leq 1$. We allow for the possibility that transferability declines in rank on the job, so $\phi'(\ell_1) \leq 0$, but we assume that

$$\frac{\partial \phi(\ell_1)\ell_1}{\partial \ell_1} > 0. \tag{C.6}$$

and that

$$\frac{\partial}{\ell_1}\{\ell_1 \phi(\ell_1)(1+h(\ell_1))\} > 0, \tag{C.7}$$

that is, workers displaced from more highly-ranked jobs enter the new job with higher rank, after accounting for both human capital accumulation and transferability.[9]

C.6 Search Costs

Workers displaced from Senior jobs should try to find a job that employs skills A and B in the same proportion as in the job that they lost, while Junior workers benefit (up to a point) from greater skill composition change. Absent search costs, workers would find jobs that make full use of their human capital, but these costs are likely to be high in the presence of large negative shocks such as large plant closures (Robinson, 2018).[10] That said, we require the following strong assumption.[11]

Assumption 7 (Search is Costly Only Radially) Once a worker encounters any job with a skill vector at angle θ_c, she can at no additional cost find a job that makes full use of her human capital up to the proportion $\phi(\ell)$, so maximizing rank on the new job entails minimizing $\Delta\theta$ for Seniors, while Juniors benefit – up to a point – from higher $\Delta\theta$.[12]

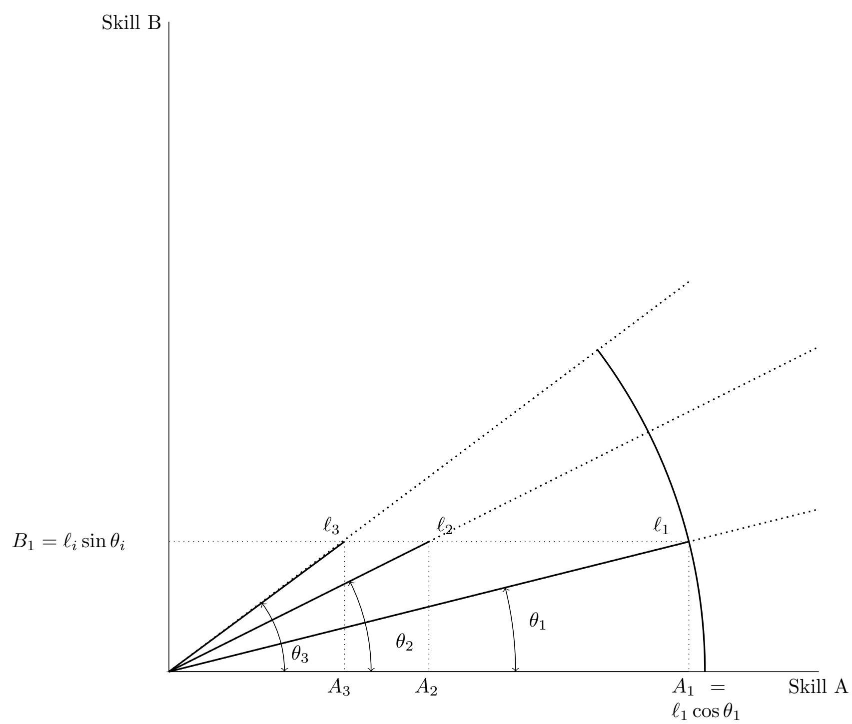

Figure C5: Theoretical Model: Greater Angular Separation Reduces Job Rank for Seniors

Figure assumes no human capital accumulation ($h(\ell) = 0$) and perfect transferability of human capital ($\phi = 1$). A Senior worker is initially employed at rank ℓ_l and skill composition (angle) θ_1. If, after being displaced, she is able to find a job along the career trajectory with angle θ_2, her rank falls to ℓ_2. If she can only find a job along the trajectory with angle $\theta_3 > \theta_2$, her rank falls further, to ℓ_3. The change in rank is more negative, the larger the change in θ.

C.7 Effects of Skill Composition Change for Senior Workers

Changes in skill composition are always deleterious for Senior workers. Consider a worker displaced from lost job $l = 1$ with skill composition θ_1 that required A_1 units of skill A and B_1 units of skill B. By hypothesis, this worker had $A_1(1+h(\ell_l))$ and $B_1(1+h(\ell_l))$ units of skills A and B, but had not yet been promoted. Absent finding a current job c with the same skill composition, either $\theta_c < \theta_l$ or $\theta_c > \theta_l$. Because the two skills are interchangeable for Seniors (but not Juniors), we assume $\theta_c > \theta_l$. Then the quantity of skill B limits the rank on the new job, depicted in Figure C5 (discussed shortly). By elementary trigonometry, the level of skill B in job j equals $B_j = \ell_j \sin\theta_j$. Taking the ratio B_c/B_l and accounting for imperfect transferability reveals the ratio of the ranks on the current and lost job to be

$$\frac{\ell_c}{\ell_l} = \phi(\ell_l)(1 + h(\ell_l))\frac{\sin\theta_l}{\sin\theta_c}, \tag{C.8}$$

which can be greater than, equal to, or less than unity. The rank of the new job can exceed the rank of the lost job when human capital investment is high, which will tend to be earlier in the career, that is, at lower (Senior) lost job ranks. However, rank can decline even if $\theta_c = \theta_l$ when ϕ is low. Subtracting unity from Equation C.8 and multiplying by ℓ_l, the change in rank equals

$$\Delta\ell = \ell_c - \ell_l = \ell_l\left(\frac{\sin\theta_l}{\sin\theta_c}\phi(\ell_l) - 1\right) + \phi(\ell_l)\ \ell_l h(\ell_l)\frac{\sin\theta_l}{\sin\theta_c}. \tag{C.9}$$

We now derive three implications by partial differentiation of Equation C.9.

Implication 1 (Magnitude of Rank Change Rises with Skill Composition Change) Noting that $\partial\sin\theta_c/\partial\theta_c = \cos\theta_c > 0$, it is sufficient to differentiate with respect to $\sin\theta_c$ to find

$$\frac{\partial\Delta\ell}{\partial\sin\theta_c} = -\ell_1\phi(\ell_l)(1 + h(\ell_l)))\frac{\sin\theta_1}{\sin^2\theta_c} < 0. \tag{C.10}$$

That is, greater skill composition change is associated with a larger decline in job rank. The situation is depicted in Figure C5, where to reduce clutter we assume no human capital investment ($h(\ell_1) = 0$) and complete transferability of human capital ($\phi = 1$). The worker is initially employed in a job of rank ℓ_l using skill composition θ_1. We compare the change in job rank that results from moving to a job with skill composition θ_3 with the change moving to a job with skill composition θ_2, where $\theta_3 > \theta_2 > \theta_1$. It is visually clear in the Figure that $\ell_3 < \ell_2$, so $\ell_3 - \ell_l < \ell_2 - \ell_l$.[13]

Implication 2 (Magnitude of Rank Change Rises in Lost Job Rank) Differentiating Equation C.9 with respect to ℓ_l yields:

$$\frac{\partial\Delta\ell}{\partial\ell_l} = \left(\frac{\sin\theta_l}{\sin\theta_c}\phi(\ell_l) - 1\right) + \phi(\ell_l)\ \frac{\partial[h(\ell_l)\ell_l]}{\partial\ell_l}\frac{\sin\theta_l}{\sin\theta_c} + \ell_l(1 + h(\ell_l))\frac{\sin\theta_1}{\sin\theta_c}\phi'(\ell) < 0. \tag{C.11}$$

Rank declines by more for workers who lose higher-rank jobs. The first term on the right hand side in parentheses is negative because $\sin\theta_l/\sin\theta_c < 1$ and $\phi(\ell_1) \leq 1$. The second term on the right hand side is negative because the rate of human capital investment declines in job rank (Equation C.4).[14] The third term on the right hand side is non-positive by Assumption 6.

The result is illustrated in Figure C6, where we compare two workers originally using skill composition θ_1, one of whom loses a job of high rank $\ell_{1,hi}$, and the other a job of low rank $\ell_{1,lo}$. The ranks of the new jobs using skill compositions 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 the high-rank job. It is visually clear that for displacement from skill composition θ_1 to skill composition 2, $|\ell_{2,hi} - \ell_{1,hi}| > |\ell_{2,lo} - \ell_{1,lo}|$.[15]

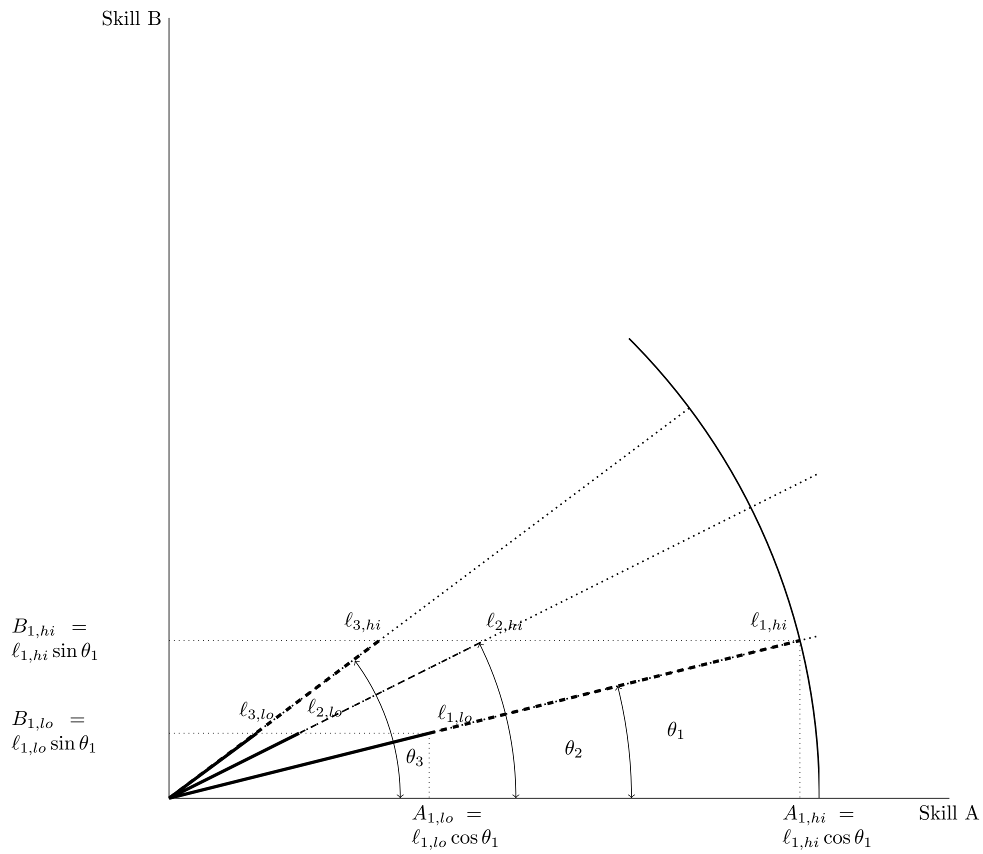

Figure C6: Theoretical Model: Effects of Lost Job Rank for Seniors

Figure assumes no human capital accumulation ($h(\ell) = 0$) and full transferability of human capital ($\phi = 1$) to reduce clutter. We compare Senior workers with high ($\ell_{1,hi}$, dotted lines) and low ($\ell_{1,lo}$, solid lines) initial ranks. For given $\Delta\theta$, the decline in rank is larger for the individual who loses the high-rank job (e.g., $\ell_{2,hi} - \ell_{1,hi} < \ell_{2,lo} - \ell_{1,lo}$) and larger Angular Separation ($\theta_3 - \theta_1$ versus $\theta_2 - \theta_1$) has a more negative effect on the higher-rank worker. See text for details.

Implication 3 (Skill Composition Change and Lost Job Rank Interact) The cross partial derivative of Equation C.10 with respect to ℓ_l equals

$$\frac{\partial^2 \Delta\ell}{\partial \sin\theta_c \partial \ell_l} = -\frac{\sin\theta_1}{\sin^2\theta_c}\frac{\partial}{\ell_1}\{\ell_1\phi(\ell_1)(1+h(\ell_1))\} < 0. \tag{C.12}$$

The partial derivative of the expression in curly brackets in Equation C.12 is positive by hypothesis (see Equation C.7.) The result can be visualized by returning to Figure C6. Noting that Equation C.12 concerns a difference-in-difference, we compare the effects of changes in θ on $\Delta\ell$ for two workers initially employed in jobs using skill composition θ_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 $(\ell_3 - \ell_l) - (\ell_2 - \ell_l) = \ell_3 - \ell_2$. It is visually obvious that $|\ell_{3,hi} - \ell_{2,hi}| > |\ell_{3,lo} - \ell_{2,lo}|$.

Implication 3 is related to Gathmann and Schönberg's (2010) observation that the accumulation of task-specific human capital with age increases the costs of distant occupational switches.

C.8 Effects of Skill Composition Change for Junior Workers

The case of Junior workers is illustrated in Figure C7. We consider a worker initially employed in a specialized task requiring A_0 units of skill A, and no B. We assume she had acquired $A_1 = A_0(1+h_0)$ units of skill A and B_1 units of skill B, making her eligible for promotion to position 1 had she not been displaced. Her rank on the lost job is $\ell_0 = \frac{A_0}{\cos\theta_0} = A_0$, where $\cos\theta_0 = \cos 0 = 1$. The best this worker can do is find a job at rank ℓ_l with $\theta = \theta_1$, as jobs with $\theta_2 < \theta_1$ do not fully use skill B, while jobs with $\theta_2 > \theta_1$ do not fully use skill A.

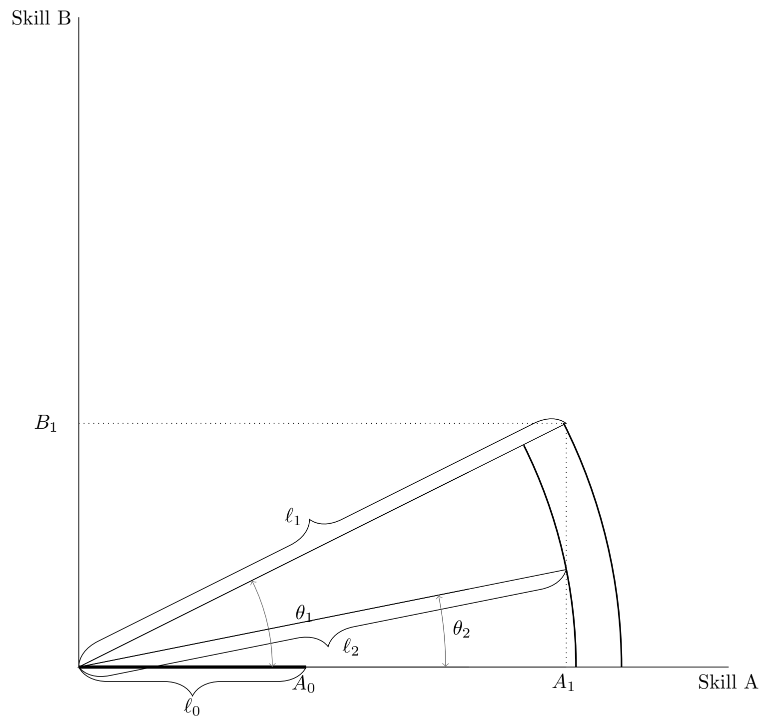

Figure C7: Theoretical Model: Skill Broadening

Junior workers can benefit from larger $\Delta\theta$ via career trajectory upgrade. Figure assumes perfect transferability of human capital ($\phi = 1$) to reduce clutter. Promotion beyond specialized job at rank ℓ_0 using A_0 units of skill A to a job at rank ℓ_l requires A_1 units of skill A and B_1 units of skill B. Rank rises even if $\theta_2 < \theta_1$ since $\ell_2 > \ell_0$, but rises even more at θ_1 because $\ell_1 > \ell_2$. The rank increase is smaller (and can even be negative) if $\theta > \theta_1$, not shown to reduce clutter. See text for details.

We typically estimate a positive but declining effect of $ANGL$ on $\Delta RANK$ for Juniors. Under the assumptions of the model to this point, it will be seen that the comparative statics predict positive effects of moderate changes in skill composition on job rank that interact positively with lost job rank ℓ_0 and negative effects of large changes in skill composition that interact negatively with lost job rank. This would require that the degree of skill composition change in the data be low for those displaced from lower-rank Junior jobs and large for those displaced from higher-rank Junior jobs, which finds only modest support in the data (see rank deciles 1 through 3 (PCT. wages) or 4 (SKL) in Table 1). To generate a positive effect of moderate skill composition change that declines in lost job rank, we modify the human capital transferability assumption.

Assumption 6A (Human Capital Transferability for Juniors) Transferability of human capital for Junior workers is a function of θ_2 as well as lost job rank ℓ_0, $\phi = \phi(\ell_0, \theta_2)$, with

$$\frac{\partial \phi(\ell_0, \theta_2)}{\partial \theta_2} \leq 0 \text{ and } \frac{\partial^2 \phi(\ell_0, \theta_2)}{\partial \ell_0 \partial \theta_2} \leq 0. \tag{C.13}$$

Intuitively, the first expression implies that a (say) welder may be able to transfer more human capital to a job with some managerial responsibility (where she oversees other welders, corresponding to a low θ_2) than to an office job (corresponding to a moderate θ_2). The second expression states that the dampening effect may be greater for an experienced welder (high ℓ_0) than a beginner welder (low ℓ_0); intuitively, the extra welding human capital is not very useful in managing.[16]

C.8 Effects for Junior Workers, $\theta_2 < \theta_1$

Supposing first that $\theta_2 \leq \theta_1$, rank on the new job equals

$$\ell_2 = \frac{\phi(\ell_0, \theta_2) A_1}{\cos \theta_2} = \frac{\phi(\ell_0, \theta_2) A_0 (1 + h(\ell_0))}{\cos \theta_2}. \tag{C.14}$$

The change in job rank equals

$$\Delta \ell = \ell_2 - \ell_0 = \ell_0 \{\phi(\ell_0, \theta_2)(1 + h(\ell_0)) \frac{1}{\cos \theta_2} - 1\}. \tag{C.15}$$

Notice that rank tends to rise because $h(\ell_0) > 0$ and $\cos \theta_2 < 1$; the only reason why an inexperienced worker would transition to a lower-ranked position is if $\phi(\ell_0) << 1$.

Implication 1A (Effect of Skill Composition Change for Junior Workers when $\theta_2 < \theta_1$) The partial derivative of Equation C.15 with respect to θ_2 equals

$$\frac{\partial \Delta \ell}{\partial \theta_2} = \ell_0 \phi(\ell_0)(1 + h(\ell_0)) \frac{\sin \theta_2}{\cos^2 \theta_2} + \frac{\ell_0 (1 + h(\ell_0))}{\cos \theta_2} \frac{\partial \phi(\ell_0, \theta_2)}{\partial \theta_2}, \tag{C.16}$$

which can be factored to yield

$$\frac{\partial \Delta \ell}{\partial \theta_2} = \frac{\ell_0(1+h(\ell_0))}{\cos\theta_2}\{\tan\theta_2 \phi(\ell_0,\theta_2) + \frac{\partial \phi(\ell_0,\theta_2)}{\partial \theta_2}\}. \tag{C.17}$$

The first term in braces is positive and the second term is non-positive, so $\partial\Delta\ell/\partial\theta_2$ will be positive provided that $\partial\phi(\ell_0,\theta_2)/\partial\theta_2$ is not too large. This Implication is visible in Figure C7 for the case in which ϕ is independent of θ_2, where it is visually obvious that $\ell_0 < \ell_2 < \ell_1$.

Implication 2A (Effect of Lost Job Rank for Junior Workers when $\theta_2 < \theta_1$) The effect of lost job rank on the change in rank is ambiguous for Junior workers. Multiplying Equation C.15 through by ℓ_0 and differentiating with respect to ℓ_0 yields

$$\frac{\partial \Delta \ell}{\partial \ell_0} = \frac{1}{\cos\theta_2}\{\frac{\partial}{\partial \ell_0}\phi(\ell_0,\theta_2)\ell_0(1+h(\ell_0))\} - 1. \tag{C.18}$$

We have already assumed that the expression in curly braces in Equation C.18 is positive (see Equation C.7), but we cannot sign the partial derivative because we do not know *a priori* whether the expression in braces divided by $\cos\theta_2$ is less than, equal to, or greater than unity. We can sign Equation C.18 in certain special cases. For example, it is positive when both $\phi(\ell_0) = 1$ and $h(\ell_0) = 0$. However, no general statements can be made without further assumptions.

Implication 3A (Interaction Between θ and ℓ_0 for Junior Workers when $\theta_2 < \theta_1$) The cross-partial derivative is given by

$$\begin{aligned}\frac{\partial^2 \Delta \ell}{\partial \ell_0 \partial \theta_2} = \frac{1}{\cos\theta_2}\{&\tan\theta_2 \frac{\partial}{\partial \ell_0}[\ell_0(1+h(\ell_0))\phi(\ell_0,\theta_2)] \\ &+ \frac{\partial \phi(\ell_0,\theta_2)}{\partial \theta_2}\frac{\partial}{\partial \ell_0}[\ell_0(1+h(\ell_0))] \\ &+ \ell_0(1+h(\ell_0))\frac{\partial^2 \phi(\ell_0,\theta_2)}{\partial \ell_0 \partial \theta_2}\}.\end{aligned} \tag{C.19}$$

The first term in braces is positive and the second two terms are non-positive. If ϕ is not a function of θ_2, then the second two terms drop out and skill composition change interacts positively with lost job rank. If the effect of skill composition change on rank change is to decline in lost job rank for Juniors as we tend to find empirically, the sum of second two terms must be sufficiently large negative. Noting that

$$\frac{\partial}{\partial \ell_0}[\ell_0(1+h(\ell_0))\phi(\ell_0,\theta_2)] = \phi(\ell_0,\theta_2)\frac{\partial}{\partial \ell_0}\ell_0(1+h(\ell_0)) + \ell_0(1+h(\ell_0))\frac{\partial \phi(\ell_0,\theta_2)}{\partial \ell_0}, \tag{C.20}$$

the algebraic sign of $\partial^2 \Delta\ell \partial\ell_0 \partial\theta_2$ depends on the sign of

$$\begin{aligned}&\frac{\partial\ell_0(1+h(\ell_0))}{\partial\ell_0}\{\tan\theta_2\phi(\ell_0,\theta_2)+\frac{\partial\phi(\ell_0,\theta_2)}{\partial\theta_2}\}\\ &+\ell_0(1+h(\ell_0))\{\tan\theta_2\frac{\partial\phi(\ell_0,\theta_2)}{\partial\ell_0}+\frac{\partial^2\phi(\ell_0,\theta_2)}{\partial\ell_0\partial\theta_2}\}\end{aligned} \tag{C.21}$$

The first term in braces must be positive for $\partial\Delta\ell/\partial\theta_2 > 0$. However, $\partial^2\Delta\ell/\partial\ell_0\partial\theta_2$ can be negative if the last term is sufficiently large negative. Notice that this last term is linear in lost job rank and so its magnitude can be large relative to that of the first term, which is a function of rates of change. However, the question is ultimately empirical.

C.8 Effects for Junior Workers, $\theta_2 > \theta_1$

When $\theta_2 > \theta_1$, the ratio of ranks on the new and old jobs can be expressed as the product of two ratios, one corresponding to the transition from job 0 to a job 1 with $\theta = \theta_1$, and the second to a transition from job 1 to a job with $\theta = \theta_2$, yielding

$$\frac{\ell_2}{\ell_0}=\frac{\ell_2}{\ell_l}\frac{\ell_l}{\ell_0}=\frac{\sin\theta_1}{\sin\theta_2}\frac{\phi(\ell_0,\theta_2)(1+h(\ell_0))}{\cos\theta_1}=\phi(\ell_0,\theta_2)(1+h(\ell_0))\frac{\tan\theta_1}{\sin\theta_2}, \tag{C.22}$$

where $\sin\theta_1/\cos\theta_1 = \tan\theta_1$. This is nearly, but not quite identical to the ratio of ranks for Senior workers in Equation C.8, the difference being the appearance of $\tan\theta_1$ in place of $\sin\theta_1$. Subtracting unity and multiplying through by ℓ_0 yields

$$\Delta\ell=\ell_0\{\phi(\ell_0,\theta_2)(1+h(\ell_0))\frac{\tan\theta_1}{\sin\theta_2}-1\} \tag{C.23}$$

Implication 4 (Comparative Statics for Junior Workers, $\theta_2 > \theta_1$) The partial derivative of $\Delta\ell$ with respect to θ_2 is

$$\frac{\partial\Delta\ell}{\partial\theta_2}=\frac{\tan\theta_1}{\sin\theta_2}\ell_0[1+h(\ell_0)]\{-\frac{\cos\theta_2}{\sin\theta_2}\phi(\ell_0,\theta_2)+\frac{\partial\phi(\ell_0,\theta_2)}{\partial\theta_2}\}<0, \tag{C.24}$$

and so has the same algebraic sign as for Seniors. The cross partial is equal to

$$\begin{aligned}\frac{\partial^2\ell}{\partial\ell_0\partial\theta_2}=\frac{\tan\theta_1}{\sin\theta_2}\{&-\frac{1}{\tan\theta_2}\frac{\partial\ell_0\phi(\ell_0,\theta_2)(1+h(\ell_0))}{\partial\ell_0}\\ &+\frac{\partial\phi(\ell_0,\theta_2)}{\partial\theta_2}\frac{\partial\ell_0(1+h(\ell_0))}{\partial\ell_0}\\ &+\ell_0(1+h(\ell_0))\frac{\partial^2\phi(\ell_0,\theta_2)}{\partial\ell_0\partial\theta_2}\}\end{aligned} \tag{C.25}$$

The first two terms in Equation C.25 are negative. The cross-partial has the same algebraic sign as for Seniors if $\partial^2\phi(\ell_0,\theta_2)/\partial\ell_0\partial\theta_2 \leq 0$, but again, this is an empirical question. Finally, the effect of ℓ_0 is

$$\frac{\partial \Delta\ell}{\partial \ell_0} = \left(\frac{\tan\theta_1}{\sin\theta_2}\phi(\ell_0,\theta_2) - 1\right) + \frac{\tan\theta_1}{\sin\theta_2}\left(\phi(\ell_0,\theta_2)\ \frac{\partial[h(\ell_0)\ell_0]}{\partial \ell_0} + \ell_0(1+h(\ell_0))\frac{\partial \phi(\ell_0,\theta_2)}{\partial \ell_0}\right). \tag{C.26}$$

Compare this expression with Equation C.11 and notice that the first term in parentheses on the right hand side of Equation C.26 involves $\tan\theta_1$ rather than $\sin\theta_1$. This term is guaranteed negative for Seniors because $\phi\sin\theta_1/\sin\theta_2 < 1$, but will be negative for Juniors only if $\phi\tan\theta_1/\sin\theta_2 < 1$. The condition does not hold if, for example, $\phi = 1$ and the promotion path at the original job entails using equal amounts of skill A and skill B, in which case $\tan\theta_1 = 1$. The condition is more likely to hold, the larger is θ_2 relative to θ_1, meaning that promotion entails "small" quantities of skill B on the job so $\tan\theta_1 << 1$. Intuitively, this condition implies that promotion does not entail moving from a job that uses only welding skills to a job using equal amounts of welding and people skills. Notice, though, that this condition is not necessary, since the second term on the right-hand-side in parentheses is negative.

Implication 5 (Comparative Statics for Junior Workers, $\theta_2 \gtreqless \theta_1$) Because we do not know whether θ_2 is greater than, equal to, or less than θ_1, the comparative statics do not yield unambiguous predictions for Junior workers. The patterns in the data depend on the distribution of job opportunities and search costs.[17] The bottom line, however, is that while greater changes in skill composition for Junior workers may not *necessarily* lead to superior labor market outcomes, our analysis makes clear that it is *possible*.

Notes

[1]There are other potential explanations. Because search is costly, younger workers are likely less well matched, and older workers, better matched to their job. However, the search cost story is arguably more a story of age (or experience), which we control for in our empirical analysis, than of lost job rank.

[2]Frederiksen and Kato (2017) find a positive relationship between the number of roles and the odds of career success as measured by the appointment to a top management position, with roles experienced internally being more important than those obtained externally, interpreted as indicating the importance of skill broadening (23). As we are looking at changes in labor market outcomes across jobs at different employers, we use the term "career trajectory upgrade" to refer to changes in skill composition that make fuller use of the worker's existing skill portfolio.

[3]Notice that rank and output are related by

$$\ell_j = B_j(1+\alpha_f^2)^{1/2} = q_j(\alpha_f^{-2}+1)^{1/2}.$$

[4]Lazear (2009) shows that the mapping of tasks into earnings is subtle, and depends on the distribution of workers' values to outside firms, ignored here.

[5] The reader may wonder whether real-world career paths might converge, in which case skill composition change could be less costly for the highest-rank Senior workers. Interestingly, Murphy (1986) shows in a 2-skill model of lifetime investment under uncertainty and unequal initial endowments, the optimal paths in general never cross (111). Ultimately, though the question is empirical.

[6] We therefore depart from the assumption of Robinson (2018), not that workers' job choices prior to displacement are optimal – otherwise, why would they have chosen the job? – but in the sense that workers are continuously employed in jobs that make full use of their human capital. He notes, too, that some mobility, especially for younger workers, will reflect life cycle accumulation of human capital on the job.

[7]Delayed promotion may help avoid the consequences of the Peter Principle (Lazear, 2004b). Also, the firms in question could be financially stressed, and hence less likely to promote (Haltiwanger et al., 2018). Indeed, Lachowska et al. (2020) and Jacobson et al. (1993) find that worker earnings dip *prior* to displacement. Finally, workers may be reluctant to "give up their place in line," and being displaced may signal that they were not separated for cause.

[8]Promotions and specific human capital investment may be complementary (Prendergast, 1993; Scoones and Bernhardt, 1998). Kwon and Milgrom (2014) infer that the significance of firm- and occupation-specific human capital rise with job rank in their study of Swedish data. Declining rank absent occupation change could also result from the Peter Principle Lazear (2004b). We ignore these possibilities here.

[9] In other words, a worker displaced from a lower-rank job never leapfrogs a worker displaced from a higher-rank job. Note that this formulation applies when A and B are differentially transferable. Let q_p denote potential output absent firm specificity. Let $\phi_a < 1$ and $\phi_b < 1$ be the fractions of skills transferable. Then actual output will be $q_c = \min[\phi_a A, \alpha_f \phi_b B] = \phi \min[A, \alpha_f B] = \phi q_p$, where $\phi = \min[\phi_a, \phi_b]$. Then observe that $\ell_c = q_c(\alpha_f^{-2}+1)^{1/2} = \phi q_p(\alpha_f^{-2}+1)^{1/2} = \phi \ell_p$, where ℓ_p is potential rank at the current firm absent limitations on transferability.

[10]This is an extension of the argument by Moscarini and Vella (2008) that directed search costs are likely to be particularly high when national unemployment is high.

[11] Cortes and Gallipoli (2018) estimate a gravity model of occupation flows and find that the cost of search is positively related to task distance as measured by Angular Separation, but that task-specific search costs are only about 6% of total search costs.

[12]This rules out the possibility that workers could be indifferent between two jobs with different $\Delta\theta$ (and identical $\Delta\ell$), in which case $\Delta\theta$ and $\Delta\ell$ would be uncorrelated. Violation of this assumption in the data works against the predictions of the model.

[13]Distant job moves will be costly even if A and B are not perfect complements. For example, Lazear (2009) allows for perfect substitutability, but investment is still unbalanced, and skill composition change still entails a loss.

[14]

$$\frac{\partial \Delta B_j}{\partial \ell_j} = \frac{\partial h(\ell_j) B_j}{\partial \ell_j} = \sin\theta_j \frac{\partial [h(\ell_j)\ell_j]}{\partial \ell_j} < 0.$$

[15]As before, the Figure assumes perfect human capital transferability and no human capital accumulation. The simplification is innocuous, as we are interested, not in rank change between the old and new job (a vector difference), but the difference in rank change (a difference-in-difference). It is visually obvious that the horizontal distance $|A_{2,hi} - A_{1,hi}|$ is larger than $|A_{2,lo} - A_{1,lo}|$. The same holds for displacement to skill composition 3.

[16] We could introduce the modified assumption regarding transferability for Senior workers but it (a) seems redundant and (b) only reinforces the comparative static results at the expense of additional algebraic clutter.

[17] For example, suppose there are just two jobs, one with $\theta_2 = \epsilon$ and the other with $\theta_2 = \theta_1 + \epsilon$, where $\epsilon > 0$. Then $\Delta\ell$ and $\Delta\theta$ are positively related. If, on the other hand, the jobs have $\theta_2 = \theta_1$ and $\theta_2 >> \theta_1$, the relationship is negative. The data likely contain a mixture of $\theta_2 < \theta_1$ and $\theta_2 > \theta_1$.

D Why Instrumental Variables Estimation

D.1 A Simple Model

We consider the potential for endogeneity of $ANGL$ for the parsimonious (or conditional on Junior-Senior status) model, shortening variable names and orthogonalizing all variables with respect to the demographics X_i, to reduce clutter. Let R_{il} denote individual i's rank on the lost job, R_{ic} rank on the current job, and A_{icl} Angular Separation between jobs l and c. The system of equations is

$$R_{il} = \epsilon_{il} \tag{D.1}$$

$$\epsilon_{ih} = \mu_i + \nu_{ih}, \quad h = l, c \tag{D.2}$$

$$R_{ic} = \beta_R R_{il} + \beta_A A_{icl} + \beta_{RA} R_{il} \times A_{icl} + \epsilon_{ic} \tag{D.3}$$

$$\Delta R_{icl} = R_{ic} - R_{il} = \beta_R R_{il} + \beta_A A_{icl} + \beta_{RA} R_{il} \times A_{icl} + \nu_{ic} - \nu_{il} \tag{D.4}$$

$$A_{icl} = \alpha_c c_{il} + \alpha_R R_{il} + \alpha_{cR} c_{il} \times R_{il} + \alpha_\mu \mu_i + \alpha_\nu \nu_{ic} + \psi_{icl} \tag{D.5}$$

Current job rank R_{ic} depends lost job rank R_{il}, Angular Separation A_{icl}, and their interaction. The error term ϵ_{ih} ($h = l, c$) is the sum of a white noise shock ν_{ih} and an unobserved, individual-level effect (ability), μ_i. The white noise term ν_{ih} is (1) serially uncorrelated for a given worker i; (2) uncorrelated with μ_i; (3) and uncorrelated across workers i and i'. We hope to identify the effects of A_{icl} that operate through R_{il} and c_{il}.

Suppose first that $\alpha_\mu = 0$ but $\alpha_\nu \neq 0$ in Equation D.5. Then a health or productivity shock ν_{ic} would be reflected in both Equations D.4 and D.5. For example, a negative shock could reduce the efficiency of job search of a Senior worker, increasing A_{icl} and reducing ΔR_{icl}. Our IV estimation employs instruments for terms involving A_{icl} with means from the Continuously Employed Sample (CE) in occupation l, with

$$\mathbf{A_{icl}} = \mathbf{\Gamma_A A_l^{CE}} + \Upsilon_{icl}. \tag{D.6}$$

By hypothesis, the means of ν_{ic} for the CE sample are uncorrelated with ν_{ic}, so IV is consistent in the sense that the shocks ν_{ic} in Equations D.4 and D.5 no longer affect the estimates.

D.1 Unobservable Worker Ability

If individuals sort into occupations based on unobservable ability, and $\alpha_\mu \neq 0$ in Equation D.5, the means $\mathbf{A_l^{CE}}$ contain means of μ_i, and IV estimates include the effects of ability. We expect sorting to bias the effects of R_{il} and $R_{il} \times A_{icl}$ towards zero for Senior workers; higher-ability Senior workers should be better able to avoid large rank changes, and the effects of rank changes should be muted. That said, we leave the question of the role of individual ability for future research.[1]

D.2 Overidentification

Although our system is just identified with two endogenous variables and two instruments, the occupation-specific mean of $ANGL$ in the Non-Displaced Sample is available as an additional instrument. We add the instrument to the two instruments based on Continuously Employed Sample means, and test the null hypothesis that the instruments can be excluded from the second stage. Selected second-stage estimates and Hansen J test statistics are contained in Tables D1 and D2. The magnitudes of the coefficients are similar to those obtained using two instruments. The Hansen J-statistics are low across the board in the Displaced Sample, and the null hypothesis of exogeneity is not rejected at the 5% level in the Plant Closure Sample; the probability value of 0.093 for ΔSKL using Comparison Sample instruments is of less concern given the probability values of 0.17 and 0.18 using Continuously Employed and Non-Plant Closure instruments. There is arguably an issue with the ΔSKL and wage change regression for the Continuously Employed and Comparison Samples, but those samples are of secondary interest.

D.3 Random Mobility Means As Instruments

D.3 Rank

In Section 4 we observed that just as in Gathmann and Schönberg (2010), the distribution of $ANGL$ in the data and under random mobility differ, but are positively correlated, raising the question whether the latter can serve as instruments for the former. The results are contained in Appendix Table D3. The first-stage Kleibergen-Paap statistics drop by an order of magnitude and the estimated coefficients on $ANGL$ and its rank interactions are generally statistically insignificant in the Displaced and Plant Closure Samples.[2] These findings are consistent with the notion that the career transitions of displaced workers reflect directed search, different from those that would be observed under random mobility, and that their search process produces results that roughly – perhaps only very roughly – mimic the transitions of the continuously employed.

D.3 Wages

Table D4 reports estimates for the wage-interaction model using the random mobility instruments. In contrast to the rank results in Section D.3, the key estimated coefficients are statistically significantly different than zero in the Displaced Sample. However, the standard errors are about 60% larger. Moreover, the estimated coefficients for the Plant Closure Sample are smaller than their standard errors, with Kleibergen-Paap F statistics using random mobility means are one-sixth their values using Continuously Employed means. $ANGL$ under random mobility, while not uncorrelated with $ANGL$ in the data, is generally a poor instrument.

Table D1: Estimated Coefficients and Overidentification Diagnostics: Rank Change Regressions

	A. Main Instruments					
	Displaced		Plant Closure		Cont's'ly Emp.	
	(1)	(2)	(3)	(4)	(5)	(6)
	ΔPCT	ΔSKL	ΔPCT	ΔSKL	ΔPCT	ΔSKL
$LPCT$	-0.6480	0.0001	-0.8228	-0.0000	-0.6597	0.0000
	(0.0804)	(0.0002)	(0.1239)	(0.0002)	(0.0794)	(0.0001)
$LSKL$	7.6897	-0.1897	7.8595	-0.1354	1.0511	-0.3075
	(1.6598)	(0.1282)	(2.5609)	(0.1361)	(1.4931)	(0.0950)
$ANGL$	0.1919	0.0003	0.0433	0.0000	0.1114	0.0003
	(0.0743)	(0.0004)	(0.1186)	(0.0004)	(0.0744)	(0.0003)
$\times LPCT$	-0.3407		-0.1186		-0.2502	
	(0.1154)		(0.1604)		(0.1186)	
$\times LSKL$		-0.0081		-0.0091		-0.0066
		(0.0020)		(0.0021)		(0.0015)
Hansen J-Statistic	0.04	0.85	0.00	1.86	0.05	5.53
J p-value	0.8451	0.3559	0.9756	0.1727	0.8272	0.0187
	B. Plant Closure Sample: Alternative Instrument Sets					
	Cont's'ly Emp.		Comparison		Non-Plant Closure	
	ΔPCT	ΔSKL	ΔPCT	ΔSKL	ΔPCT	ΔSKL
$LPCT$	-0.8228	-0.0000	-0.7803	-0.0000	-0.5562	-0.0000
	(0.1239)	(0.0002)	(0.1025)	(0.0002)	(0.1258)	(0.0002)
$LSKL$	7.8595	-0.1354	7.9458	-0.0726	8.0353	-0.1231
	(2.5609)	(0.1361)	(2.5446)	(0.1427)	(2.5885)	(0.1702)
$ANGL$	0.0433	0.0000	0.0771	-0.0000	0.3058	0.0000
	(0.1186)	(0.0004)	(0.0994)	(0.0004)	(0.1305)	(0.0004)
$\times LPCT$	-0.1186		-0.1790		-0.4888	
	(0.1604)		(0.1344)		(0.1647)	
$\times LSKL$		-0.0091		-0.0100		-0.0093
		(0.0021)		(0.0022)		(0.0027)
Hansen J-Statistic	0.00	1.86	0.08	2.82	0.11	1.74
J p-value	0.9756	0.1727	0.7809	0.0929	0.7393	0.1870

The J tests are carried out by augmenting the instruments to include the Non-Displaced sample mean of $ANGL$. Continuously Employed means serve as instruments for the Displaced and Plant Closure Samples, and Displaced Means serve as instruments for the Continuously Employed Sample.

Table D2: : Overidentification Diagnostics: Earnings Change Regressions

	Displaced	Plant Closure	Comparison
	(1)	(2)	(3)
W	-0.1407	-0.2346	-0.4454
	(0.0551)	(0.0975)	(0.0144)
$ANGL$	0.0315	0.0207	0.0072
	(0.0057)	(0.0091)	(0.0018)
$\times W$	-0.0047	-0.0031	-0.0012
	(0.0008)	(0.0013)	(0.0003)
Hansen J-Statistic	1.01	1.08	4.92
J p-value	0.3158	0.2991	0.0266

The J tests are carried out by augmenting the instruments to include the Non-Displaced sample mean of $ANGL$. Continuously Employed means serve as instruments for the Displaced and Plant Closure Samples, and Displaced Means serve as instruments for the Comparison Sample.

Table D3: ΔPCT and ΔSKL Regressions: IV Estimates Using Random Mobility Instruments

	Displaced Sample		Plant Closure Sample		Cont'sly Emp. Sample	
	(1)	(2)	(3)	(4)	(5)	(6)
	CE	Random	CE	Random	DW	Random
A. Δ *PCT* Models						
ANGL	0.2036	-0.1065	0.0473	-0.2516	0.1290	-0.0635
	(0.0763)	(0.1419)	(0.1184)	(0.2124)	(0.0889)	(0.1041)
× *LPCT*	-0.3549	-0.0860	-0.1297	0.2530	-0.2732	-0.0790
	(0.1168)	(0.2000)	(0.1601)	(0.3054)	(0.1252)	(0.1427)
Endog P-Val	.0953	.03721	.08033	.0649	.09993	.002697
Kleibergen-Paap F	110.26	17.07	69.07	6.82	88.04	39.52
Observations	11770	11774	4398	4400	41995	42062
B. Δ *SKL* Models						
ANGL	0.0003	-0.0001	-0.0001	0.0003	0.0002	0.0002
	(0.0004)	(0.0009)	(0.0004)	(0.0011)	(0.0003)	(0.0004)
× *LSKL*	-0.0082	-0.0039	-0.0092	-0.0061	-0.0057	-0.0029
	(0.0020)	(0.0050)	(0.0021)	(0.0065)	(0.0013)	(0.0026)
Endog P-Val	.03036	.009944	.4018	.06598	.0000151	8.25e-06
Kleibergen-Paap F	69.10	4.79	26.83	3.42	42.34	10.96
Observations	11770	11774	4398	4400	41995	42062

Expected values of $ANGL$ under random mobility replace Continuously Employed (CE) instruments in cols. 2 and 4 and Displaced instruments in col. 6. See Section D.3 for details.

Table D4: Wage Regression: IV Estimates Using Random Mobility Instruments

	Displaced Sample		Plant Closure Sample		Comparison Sample	
	(1)	(2)	(3)	(4)	(5)	(6)
	CE	Random	CE	Random	DW	Random
$ANGL$	0.0300	0.0482	0.0199	0.0318	0.0062	0.0190
	(0.0056)	(0.0107)	(0.0091)	(0.0165)	(0.0019)	(0.0052)
$\times W$	-0.0045	-0.0071	-0.0030	-0.0048	-0.0011	-0.0028
	(0.0008)	(0.0015)	(0.0013)	(0.0023)	(0.0003)	(0.0007)
Endog P-Val	.0008117	.0004034	.2829	.2201	.1955	.004903
Kleibergen-Paap F	60.55	7.98	35.89	4.37	60.32	8.37
Observations	9586	9589	3519	3521	196288	196540

Expected values of $ANGL$ under random mobility replace Continuously Employed (CE) instruments in cols. 2 and 4 and Displaced instruments in col. 6. See Section D.3 for details.

Notes

[1]We also ignore the issue of unobservable ability *within* occupations (Blien et al., 2019).

[2] Only in the ΔSKL models estimated on the Continuously Employed Sample are the estimated coefficients on the interaction terms negative and statistically significant, but even here, the IV Kleibergen-Paap F statistic falls from 42.34 to 10.41, and the standard error is twice as large.

E Supplement: Rank Change Regression Analysis

This section contains a variety of results not contained in the body of the paper to save space. Full regression results for the **parsimonious model** (Equation 7) are presented in Tables E1 and E2. As they are unremarkable, we do not comment on them here. We suppress the estimated coefficients from the **Junior-Senior model**, but report the diagnostic statistics in Table E3. The Figure in the text reported results for just one PCT and one SKL cutoff; Figure E1 shows results for a wider range of cutoffs. The main takeaway from these Figures is that both the career trajectory upgrade and task specificity stories remain intact at a range of cutoffs. Finally, the pattern of predicted effects for the **Comparison Samples**, shown in Figure E2, resembles that of displaced workers.

E.1 Partial Derivatives of Equation 7

The partial derivative of Equation 7 with respect to $ANGL$ is

$$\frac{\partial \Delta PCT_{icl}}{\partial ANGL_{icl}} = \beta_A + \beta_{PA} \times LPCT_{il}, \tag{E.1}$$

and the cross-partial derivative with respect to $LPCT_{il}$, by

$$\frac{\partial^2 \Delta PCT_{icl}}{\partial ANGL_{icl} \partial LPCT_{il}} = \beta_{PA}. \tag{E.2}$$

Finally, the partial derivative of Equation 7 with respect to $LPCT_{il}$ yields

$$\frac{\partial \Delta PCT_{icl}}{\partial LPCT_{il}} = \beta_P + \beta_{PA} ANGL_{icl}, \tag{E.3}$$

Finding career trajectory upgrade in ΔPCT models requires $\hat{\beta}_A > 0$, but is not necessary in the case of the ΔSKL models because $LSKL$ takes on negative values at lower ranks – see Table 1.

Table E1: ΔPCT Full Regression Results: OLS and IV Estimates

	Displaced Sample		Plant Closure Sample		Cont'sly Employed	
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
$LPCT$	-0.5602	-0.6371	-0.6357	-0.8145	-0.4755	-0.6465
	(0.0472)	(0.0818)	(0.0621)	(0.1236)	(0.0437)	(0.0879)
$LSKL$	7.3954	7.5678	8.8408	7.9415	0.1221	-0.1813
	(1.6321)	(1.6622)	(2.3161)	(2.5418)	(1.7421)	(1.7749)
$ANGL$	0.1901	0.2036	0.1255	0.0473	0.2566	0.1290
	(0.0486)	(0.0763)	(0.0613)	(0.1184)	(0.0395)	(0.0889)
$\times LPCT/100$	-0.4856	-0.3549	-0.3989	-0.1297	-0.5424	-0.2732
	(0.0723)	(0.1168)	(0.0881)	(0.1601)	(0.0629)	(0.1252)
Tenure 1-3 Years	0.9356	1.0134	2.3998	2.6157		
	(0.6205)	(0.6438)	(1.1264)	(1.1269)		
Tenure 3-10 Years	2.2070	2.0883	3.4629	3.3716		
	(0.5857)	(0.6124)	(1.0980)	(1.1209)		
Tenure 11-20 Years	1.6236	1.5530	2.4803	2.3279		
	(0.8985)	(0.9007)	(1.5045)	(1.5345)		
Tenure 20+ Years	1.1572	1.0190	3.5578	3.1427		
	(1.1836)	(1.2010)	(1.8043)	(1.8323)		
Displaced 1 Year Ago	-1.4088	-1.4229	-0.5997	-0.5352		
	(0.5800)	(0.5954)	(0.8887)	(0.8985)		
Displaced 3 Years Ago	-0.1218	-0.2021	0.1130	0.1577		
	(0.5955)	(0.6062)	(0.9389)	(0.9661)		
Displaced Years Unknown	0.5290	1.6065	2.0525	4.1086		
	(3.6285)	(3.5153)	(6.9154)	(6.9507)		
Age 20-24	-4.0069	-4.2040	-1.7376	-2.2492	-4.2891	-4.4221
	(0.9756)	(0.9917)	(1.6625)	(1.6919)	(0.6964)	(0.7042)
Age 25-34	-0.0965	-0.2707	0.0333	-0.2090	-0.9037	-0.9769
	(0.6238)	(0.6181)	(0.9606)	(0.9897)	(0.3418)	(0.3549)
Age 45-54	0.0678	0.2940	0.8176	1.1962	-0.1142	-0.1886
	(0.6280)	(0.6290)	(0.9386)	(0.9172)	(0.3095)	(0.3134)
Age 55-64	-0.8799	-0.7426	-1.4297	-1.2350	-1.6682	-1.8085
	(0.8517)	(0.8592)	(1.3147)	(1.3178)	(0.4800)	(0.4658)
Female	-4.2378	-4.1616	-5.3660	-5.3762	-6.2793	-6.1610
	(0.6649)	(0.7033)	(0.9690)	(1.0462)	(0.4494)	(0.4607)
Black	-5.0761	-5.1137	-6.2693	-6.3856	-3.4427	-3.5833
	(0.8510)	(0.8670)	(1.3189)	(1.3502)	(0.4933)	(0.4915)
Hispanic	-2.9020	-2.7519	-1.6209	-1.7265	-3.2836	-3.3948
	(0.8263)	(0.8235)	(1.2059)	(1.2431)	(0.4964)	(0.5036)
Other race	-2.3931	-2.0307	-2.8147	-2.8512	-2.0995	-2.2862
	(1.1402)	(1.1459)	(1.6488)	(1.5956)	(0.5477)	(0.5493)
Educ: Dropout	-3.0038	-2.5062	-3.6584	-3.4777	-3.5372	-3.5204
	(1.0079)	(1.0098)	(1.5119)	(1.5239)	(0.7119)	(0.7544)
Educ: Assoc Deg	3.8393	3.9186	3.9557	4.1127	2.2180	2.2526
	(0.8367)	(0.7871)	(1.4819)	(1.4367)	(0.5134)	(0.5139)
Educ: Some Coll	0.3672	0.2835	0.2407	0.1436	1.5343	1.6411

	(0.7075)	(0.6998)	(1.0352)	(1.0356)	(0.4251)	(0.4295)
Educ: Coll Grad	4.0453	5.5043	4.5264	6.4691	2.2320	3.0642
	(0.8860)	(0.9207)	(1.1452)	(1.2861)	(0.7296)	(0.6855)
Constant	39.0432	36.8241	43.5818	48.1114	36.0616	44.3930
	(3.3097)	(5.7959)	(4.9537)	(9.7561)	(3.7339)	(7.1256)
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
Endog Chi-Sq		4.702		5.043		4.606
Endog P-Val		.0953		.08033		.09993
Kleibergen-Paap F		110		69		88
Observations	11774	11770	4400	4398	42120	41995
R-Square	.4629	.4531	.4697	.4566	.4435	.4368

This table shows full results for the ΔPCT regressions. Standard errors clustered on IPUMS 1990 occupation. Regressions in columns 2 and 4 use Continuously Employed Sample means of $ANGL$ and $ANGL \times LPCT$ as instruments, and regression in columns 6 uses Displaced Sample means.

Table E2: ΔSKL Full Regression Results: OLS and IV Estimates

	Displaced Sample		Plant Closure Sample		Cont'sly Employed	
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
$LPCT$	0.0000	0.0001	-0.0000	-0.0000	-0.0000	-0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)
$LSKL$	0.0062	-0.1814	0.0329	-0.1272	0.0431	-0.3563
	(0.0306)	(0.1267)	(0.0321)	(0.1357)	(0.0304)	(0.0850)
$ANGL$	-0.0003	0.0003	-0.0002	-0.0001	0.0001	0.0002
	(0.0001)	(0.0004)	(0.0001)	(0.0004)	(0.0001)	(0.0003)
$\times LSKL$	-0.0112	-0.0082	-0.0116	-0.0092	-0.0120	-0.0057
	(0.0004)	(0.0020)	(0.0005)	(0.0021)	(0.0004)	(0.0013)
Tenure 1-3 Years	0.0076	0.0082	-0.0043	-0.0042		
	(0.0039)	(0.0040)	(0.0077)	(0.0078)		
Tenure 3-10 Years	0.0070	0.0059	-0.0031	-0.0046		
	(0.0046)	(0.0048)	(0.0082)	(0.0082)		
Tenure 11-20 Years	0.0033	0.0027	-0.0094	-0.0115		
	(0.0056)	(0.0057)	(0.0104)	(0.0103)		
Tenure 20+ Years	0.0003	-0.0016	-0.0081	-0.0110		
	(0.0074)	(0.0077)	(0.0102)	(0.0105)		
Displaced 1 Year Ago	-0.0071	-0.0073	-0.0049	-0.0049		
	(0.0029)	(0.0030)	(0.0051)	(0.0051)		
Displaced 3 Years Ago	0.0038	0.0038	0.0051	0.0053		
	(0.0032)	(0.0032)	(0.0049)	(0.0048)		
Displaced Years Unknown	0.0175	0.0233	-0.0306	-0.0273		
	(0.0280)	(0.0273)	(0.0579)	(0.0571)		
Age 20-24	-0.0277	-0.0286	-0.0307	-0.0308	-0.0218	-0.0225
	(0.0057)	(0.0059)	(0.0099)	(0.0101)	(0.0038)	(0.0040)
Age 25-34	-0.0072	-0.0082	-0.0064	-0.0077	-0.0048	-0.0057
	(0.0039)	(0.0041)	(0.0065)	(0.0067)	(0.0022)	(0.0024)
Age 45-54	-0.0059	-0.0050	-0.0105	-0.0096	-0.0035	-0.0038
	(0.0038)	(0.0038)	(0.0057)	(0.0057)	(0.0019)	(0.0018)
Age 55-64	-0.0116	-0.0115	-0.0301	-0.0317	-0.0071	-0.0082
	(0.0053)	(0.0052)	(0.0075)	(0.0075)	(0.0029)	(0.0028)
Female	-0.0065	-0.0088	-0.0086	-0.0112	-0.0079	-0.0141
	(0.0058)	(0.0058)	(0.0069)	(0.0070)	(0.0043)	(0.0040)
Black	-0.0299	-0.0322	-0.0428	-0.0446	-0.0394	-0.0436
	(0.0054)	(0.0058)	(0.0074)	(0.0076)	(0.0033)	(0.0033)
Hispanic	-0.0212	-0.0219	-0.0322	-0.0344	-0.0237	-0.0284
	(0.0052)	(0.0054)	(0.0076)	(0.0073)	(0.0029)	(0.0030)
Other race	-0.0148	-0.0136	-0.0240	-0.0264	-0.0127	-0.0154
	(0.0088)	(0.0089)	(0.0115)	(0.0115)	(0.0039)	(0.0041)
Educ: Dropout	-0.0358	-0.0355	-0.0421	-0.0437	-0.0424	-0.0469
	(0.0054)	(0.0061)	(0.0083)	(0.0086)	(0.0052)	(0.0049)
Educ: Assoc Deg	0.0679	0.0694	0.0619	0.0626	0.0597	0.0639
	(0.0055)	(0.0056)	(0.0072)	(0.0073)	(0.0035)	(0.0038)
Educ: Some Coll	0.0403	0.0410	0.0433	0.0442	0.0392	0.0433

	(0.0044)	(0.0046)	(0.0067)	(0.0066)	(0.0027)	(0.0028)
Educ: Coll Grad	0.1212	0.1373	0.1216	0.1321	0.1125	0.1335
	(0.0066)	(0.0071)	(0.0073)	(0.0106)	(0.0054)	(0.0051)
Constant	-0.0419	-0.0859	-0.0192	-0.0286	-0.0154	-0.0160
	(0.0158)	(0.0319)	(0.0208)	(0.0374)	(0.0164)	(0.0264)
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
Endog Chi-Sq		6.989		1.824		22.2
Endog P-Val		.03036		.4018		.0000151
Kleibergen-Paap F		69		27		42
Observations	11774	11770	4400	4398	42120	41995
R-Square	.4871	.4694	.4993	.4918	.5149	.4715

This table shows full results for the ΔSKL regressions. Standard errors clustered on IPUMS 1990 occupation. Regressions in columns 2 and 4 use Continuously Employed Sample means of $ANGL$ and $ANGL \times LSKL$ as instruments, and regression in columns 6 uses Displaced Sample means.

Table E3: Diagnostic Tests of ΔPCT and ΔSKL Models, Junior-Senior Specification

				PCT Models						
JR	Displaced Sample					Plant Closure Sample				
Cut	Endog	IV: EQ	RMSE	OLS: EQ	RMSE	Endog	IV: EQ	RMSE	OLS: EQ	RMSE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1	0.239	0.121	24.928	0.171	24.744	0.220	0.167	24.770	0.084	24.544
2	0.318	0.023	24.885	0.043	24.736	0.328	0.210	24.722	0.010	24.538
3	0.177	0.009	24.894	0.189	24.732	0.193	0.396	24.713	0.246	24.529
4	0.063	0.092	24.986	0.640	24.747	0.129	0.008	24.808	0.093	24.529
5	0.153	0.208	24.952	0.546	24.747	0.189	0.049	24.757	0.188	24.539
6	0.167	0.012	24.923	0.069	24.738	0.282	0.040	24.750	0.067	24.534
7	0.262	0.115	24.910	0.070	24.736	0.234	0.053	24.753	0.109	24.540
8	0.248	0.496	24.939	0.150	24.736	0.259	0.096	24.775	0.121	24.538
9	0.027	0.000	25.039	0.005	24.722	0.037	0.000	25.525	0.004	24.523
				SKL Models						
1	0.023	0.270	0.152	0.804	0.149	0.259	0.226	0.150	0.174	0.149
2	0.007	0.096	0.153	0.381	0.149	0.085	0.169	0.150	0.322	0.149
3	0.012	0.380	0.152	0.827	0.149	0.028	0.799	0.150	0.848	0.149
4	0.018	0.061	0.151	0.124	0.149	0.064	0.031	0.149	0.193	0.149
5	0.021	0.990	0.151	0.470	0.149	0.022	0.685	0.150	0.763	0.149
6	0.003	0.671	0.152	0.154	0.149	0.053	0.425	0.150	0.160	0.149
7	0.008	0.858	0.152	0.408	0.149	0.045	0.453	0.149	0.024	0.149
8	0.012	0.068	0.154	0.093	0.149	0.352	0.728	0.151	0.048	0.149
9	0.023	0.335	0.153	0.039	0.149	0.606	0.736	0.150	0.010	0.149

Diagnostics for JR-SR rank change models (Equation 8). Endogeneity pvals: cols. 1, 6; JR-SR equality pvals (see Equation 9): 2, 4, 7, 9; root means square errors: cols. 3, 5, 8, 10.

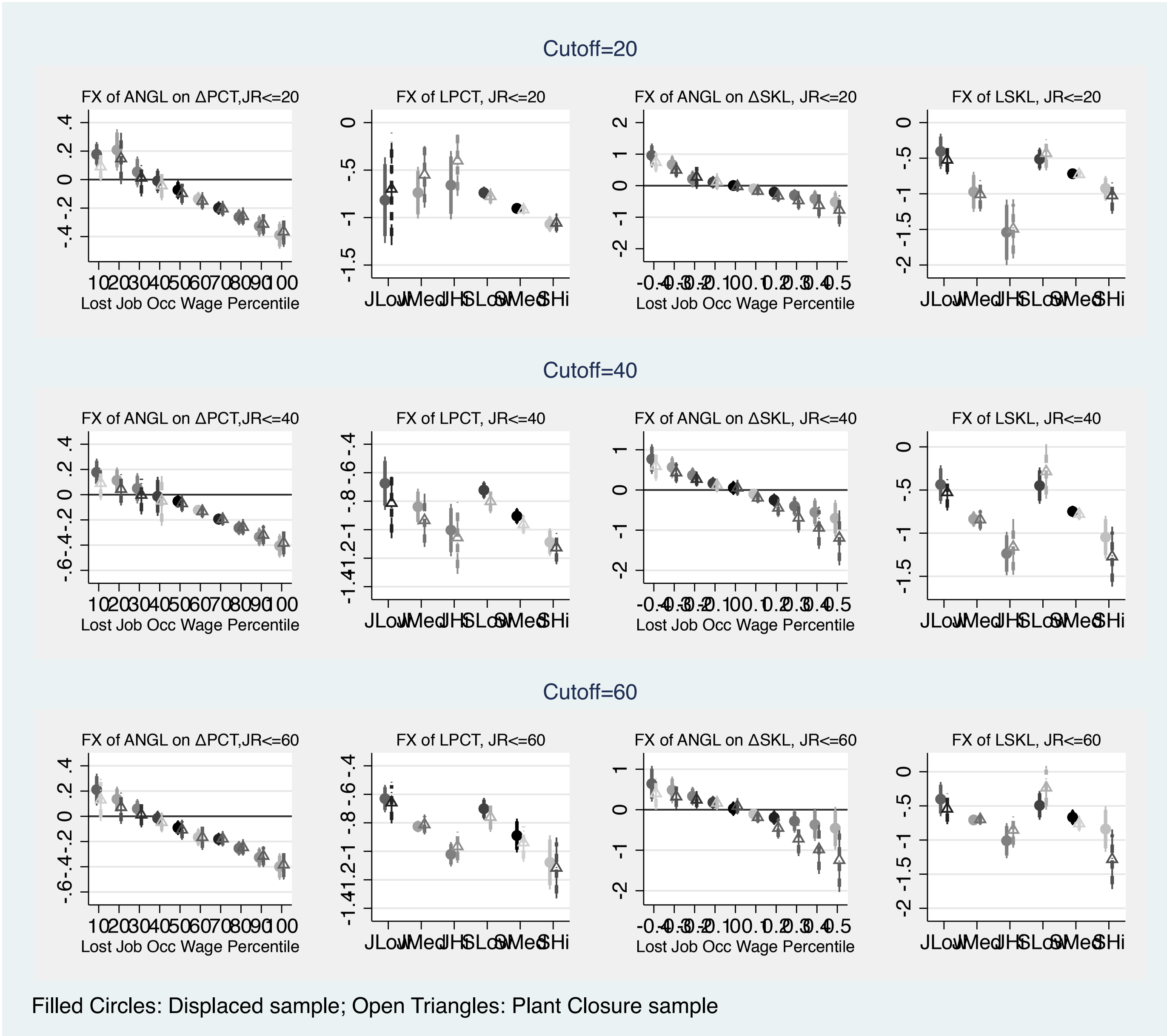

Figure E1: Predicted Effects of Lost Job Rank and $ANGL$ on ΔPCT and ΔSKL

Filled circles = Displaced Sample, Open triangles=Plant Closure Sample. Predicted effects and 90/95% confidence intervals of std. dev. increase in $ANGL$ and $LPCT/LSKL$ (Eqn. 7 and its ΔSKL analog). Effects of $LPCT/LSKL$ evaluated at medium (mean), low, and high (minus/plus 1 std. dev.) $ANGL$. Units=std. devs. of $LPCT$ and $LSKL$.

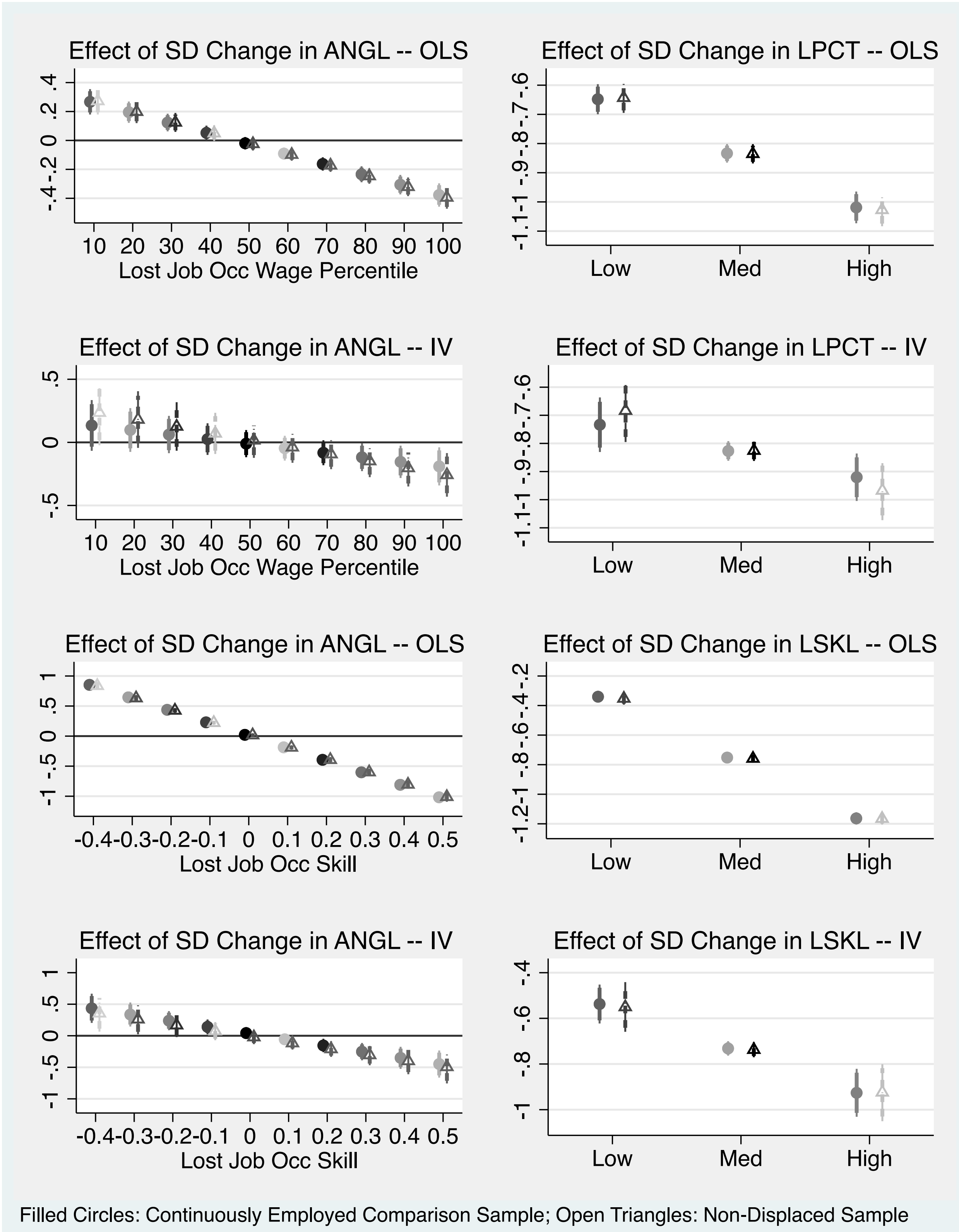

Figure E2: Predicted Effects, Comparison and Non-Displaced Samples: ΔPCT Models

Filled circles = Continuously Employed Sample, Open triangles=Non-Displaced Sample. Predicted effects and 90/95% confidence intervals of a standard deviation increase in $ANGL$ (left-hand figures) and $LPCT$ (right-hand figures). Units are standard deviations of $LPCT$. IV effects are based on Displaced Sample instruments.

Notes

[1]We also ignore the issue of unobservable ability *within* occupations (Blien et al., 2019).

[2] Only in the ΔSKL models estimated on the Continuously Employed Sample are the estimated coefficients on the interaction terms negative and statistically significant, but even here, the IV Kleibergen-Paap F statistic falls from 42.34 to 10.41, and the standard error is twice as large.

F Supplement: Wage-Interaction Models

Full regression results for estimation of the **Parsimonious Wage-Interaction** specification in Equation 11 are unremarkable, and so are presented without comment in Table F1. The **Junior-Senior** specification of the Wage-Interaction Model is given by

$$\begin{aligned}
\Delta W_{icl} = \beta_0 + \beta_P LPCT_{ic} + \beta_S LSKL_{ic} + \\
I(JR) \times \{\beta_{WJ} W_{il} + \beta_{AJ} ANGL_{icl} + \beta_{WAJ} ANGL_{icl} \times W_{il}\} \\
+ I(SR) \times \{\beta_{WS} W_{il} + \beta_{AS} ANGL_{icl} + \beta_{WAS} ANGL_{icl} \times W_{il}\} \\
+ \beta_X X_i + \Delta \epsilon_{icl},
\end{aligned} \tag{F.1}$$

Again, we suppress the estimated coefficients and report the diagnostics in Table F2. The null hypothesis of exogeneity is rejected only for the Displaced Sample. Because equality of the Junior and Senior coefficients (Equation 9) is rejected at most cutoffs, we show predicted effects at a variety of cutoffs in Figure 6 in the main paper.

Table F1: Wage Change Regressions: Wage-Interaction Model, All Coefficients

	Displaced		Plant Closure		Comparison	
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
W	-0.3396	-0.1562	-0.3542	-0.2420	-0.4413	-0.4530
	(0.0226)	(0.0549)	(0.0330)	(0.0972)	(0.0073)	(0.0154)
$ANGL$	0.0107	0.0300	0.0082	0.0199	0.0077	0.0062
	(0.0017)	(0.0056)	(0.0029)	(0.0091)	(0.0007)	(0.0019)
$\times W$	-0.0018	-0.0045	-0.0014	-0.0030	-0.0012	-0.0011
	(0.0003)	(0.0008)	(0.0004)	(0.0013)	(0.0001)	(0.0003)
$LPCT$	0.0002	0.0003	-0.0002	-0.0001	0.0009	0.0008
	(0.0002)	(0.0002)	(0.0004)	(0.0004)	(0.0001)	(0.0002)
$LSKL$	0.1843	0.1507	0.1788	0.1432	0.2289	0.2248
	(0.0398)	(0.0399)	(0.0564)	(0.0653)	(0.0169)	(0.0174)
Tnr 1-3 Y	0.0322	0.0356	0.0270	0.0292		
	(0.0112)	(0.0109)	(0.0194)	(0.0186)		
Tnr 3-10 Y	0.0225	0.0259	0.0344	0.0378		
	(0.0127)	(0.0122)	(0.0214)	(0.0206)		
Tnr 11-20 Y	-0.0229	-0.0174	-0.0289	-0.0252		
	(0.0174)	(0.0170)	(0.0223)	(0.0216)		
Tnr 20+ Y	-0.0298	-0.0232	0.0098	0.0117		
	(0.0246)	(0.0248)	(0.0399)	(0.0383)		
Dsp 1 Y Ago	-0.0201	-0.0173	0.0070	0.0123		
	(0.0098)	(0.0103)	(0.0175)	(0.0174)		
Dsp 3 Y Ago	0.0100	0.0100	0.0257	0.0287		
	(0.0110)	(0.0114)	(0.0157)	(0.0162)		
Age 20-24	-0.0438	-0.0484	-0.0344	-0.0399	-0.1730	-0.1722
	(0.0153)	(0.0164)	(0.0251)	(0.0250)	(0.0070)	(0.0068)
Age 25-34	-0.0146	-0.0135	-0.0289	-0.0297	-0.0731	-0.0727
	(0.0106)	(0.0106)	(0.0176)	(0.0180)	(0.0037)	(0.0037)
Age 45-54	-0.0125	-0.0138	-0.0109	-0.0122	0.0063	0.0062
	(0.0128)	(0.0126)	(0.0204)	(0.0199)	(0.0026)	(0.0026)
Age 55-64	-0.0392	-0.0383	-0.0753	-0.0731	-0.0045	-0.0048
	(0.0161)	(0.0157)	(0.0216)	(0.0210)	(0.0031)	(0.0032)
Female	-0.0738	-0.0695	-0.0843	-0.0823	-0.1193	-0.1190
	(0.0105)	(0.0106)	(0.0161)	(0.0159)	(0.0040)	(0.0042)
Black	-0.0928	-0.0932	-0.0976	-0.0987	-0.0793	-0.0790
	(0.0150)	(0.0152)	(0.0229)	(0.0233)	(0.0048)	(0.0047)
Hispanic	-0.0343	-0.0263	-0.0272	-0.0252	-0.0556	-0.0565
	(0.0133)	(0.0141)	(0.0200)	(0.0201)	(0.0042)	(0.0043)
Other race	-0.0026	0.0008	-0.0017	0.0026	-0.0222	-0.0230
	(0.0211)	(0.0212)	(0.0357)	(0.0359)	(0.0054)	(0.0054)
Ed: Drpt	-0.0836	-0.0721	-0.0829	-0.0768	-0.1156	-0.1201
	(0.0161)	(0.0172)	(0.0237)	(0.0237)	(0.0047)	(0.0058)
Ed: A. Deg	0.0707	0.0713	0.0774	0.0778	0.0644	0.0655
	(0.0161)	(0.0168)	(0.0257)	(0.0261)	(0.0044)	(0.0046)
Ed: S. Coll	0.0194	0.0150	0.0422	0.0393	0.0496	0.0504

	(0.0103)	(0.0104)	(0.0157)	(0.0159)	(0.0036)	(0.0035)
Ed: C. Grad	0.1866	0.1895	0.2246	0.2278	0.2160	0.2123
	(0.0117)	(0.0127)	(0.0222)	(0.0221)	(0.0073)	(0.0068)
Constant	2.1997	0.8408	2.3077	1.4679	2.9910	3.1195
	(0.1511)	(0.3793)	(0.2256)	(0.6681)	(0.0501)	(0.1201)
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
Endog Chi-Sq		14.23		2.525		3.264
Endog P-Val		.0008117		.2829		.1955
Kleibergen-Paap F		61		36		60
Observations	9589	9586	3521	3519	196829	196288

This Table contains coefficients for estimates of Equation 11 on the Earnings Samples. Abbreviations: "CE" = Continuously Employed Sample instruments; "DW" = Displaced Sample instruments; "Tnr" = Tenure on lost job; "Dsp" = Displaced "Y" ="Year," "Drpt" = high school dropout, "A. Deg"=Associate College Degree; "S. Coll"=some college; "C. Grad"=college graduate. Standard errors clustered on IPUMS 1990 occupation are in parentheses.

Table F2: Diagnostic Tests of Junior-Senior Wage-Interaction Models

Decile	Displaced Sample					Plant Closure Sample				
Cutoff	Endog	EQ, IV	RMSE	EQ, LS	RMSE	Endog	EQ, IV	RMSE	EQ, LS	RMSE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1	0.000	0.000	0.395	0.000	0.390	0.166	0.005	0.381	0.014	0.377
2	0.000	0.000	0.394	0.000	0.389	0.563	0.006	0.377	0.002	0.377
3	0.001	0.000	0.394	0.000	0.390	0.322	0.021	0.380	0.042	0.378
4	0.000	0.000	0.394	0.000	0.390	0.329	0.018	0.379	0.032	0.378
5	0.000	0.000	0.394	0.000	0.390	0.393	0.027	0.378	0.028	0.378
6	0.001	0.000	0.394	0.000	0.390	0.167	0.051	0.379	0.005	0.377
7	0.003	0.000	0.394	0.000	0.390	0.044	0.019	0.380	0.012	0.378
8	0.006	0.134	0.394	0.000	0.390	0.183	0.196	0.379	0.053	0.378
9	0.008	0.215	0.395	0.000	0.390	0.497	0.572	0.378	0.314	0.378

This table contains diagnostic tests – mostly probability values – for the JR-SR wage-interaction models (Equation F.1), by decile cutoff. Endogeneity tests are in cols. 1, 6; tests of JR-SR coefficient equality (see Equation 9): IV in cols. 2, 7 and OLS in 4, 9; and root means square errors: IV in cols. 3, 8, and OLS in cols. 5, 10. Results for the Displaced Sample are contained in columns 1-5 and for the Plant Closure Sample in columns 6-10.

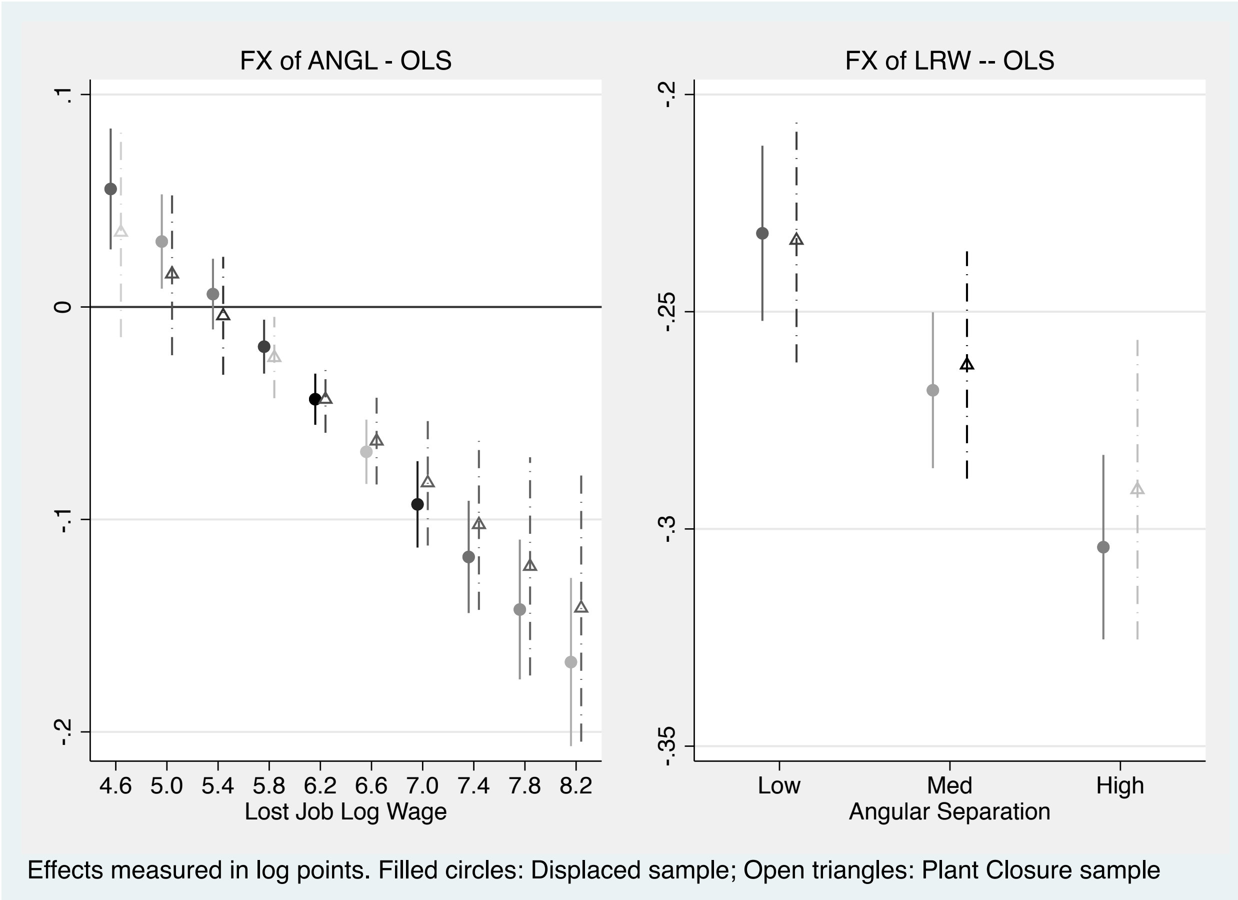

Figure F1: OLS Predicted Effects, Wage-Interaction Model: Displaced and Plant Closure Samples

Filled circles = Displaced Sample, open triangles=Plant Closure Sample. OLS predicted effects and 90/95% confidence intervals from Equation 11 of a standard deviation increase in $ANGL$ and lost job real wage evaluated at medium (mean), low, and high (minus/plus 1 std. dev.) $ANGL$.

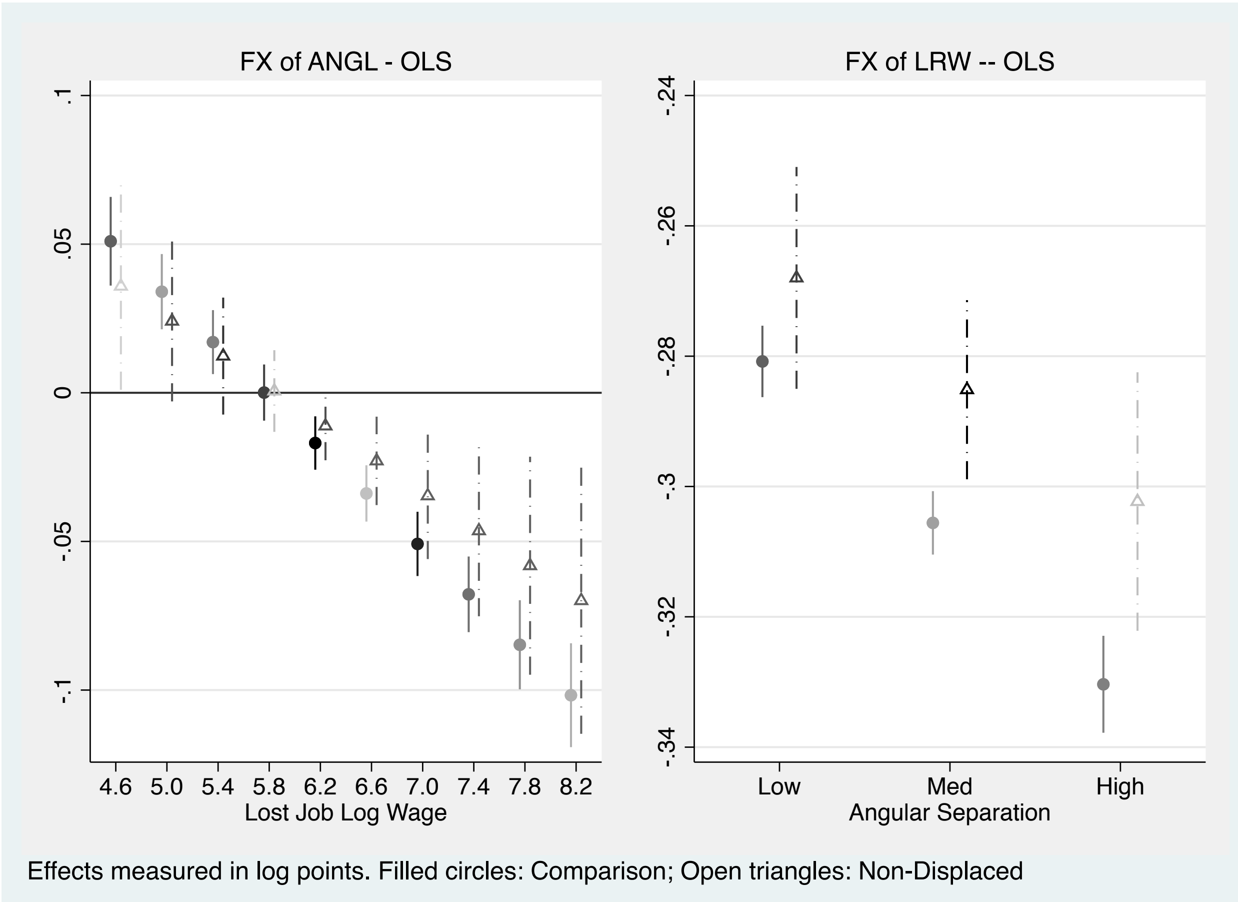

Figure F2: OLS Predicted Effects, Wage-Interaction Model: Comparison and Non-Displaced Samples

Filled circles = Comparison, open triangles=Non-Displaced Sample. IV predicted effects and 90/95% confidence intervals from Equation 11 of a standard deviation increase in $ANGL$ and lost job real wage evaluated at medium (mean), low, and high (minus/plus 1 std. dev.) $ANGL$.

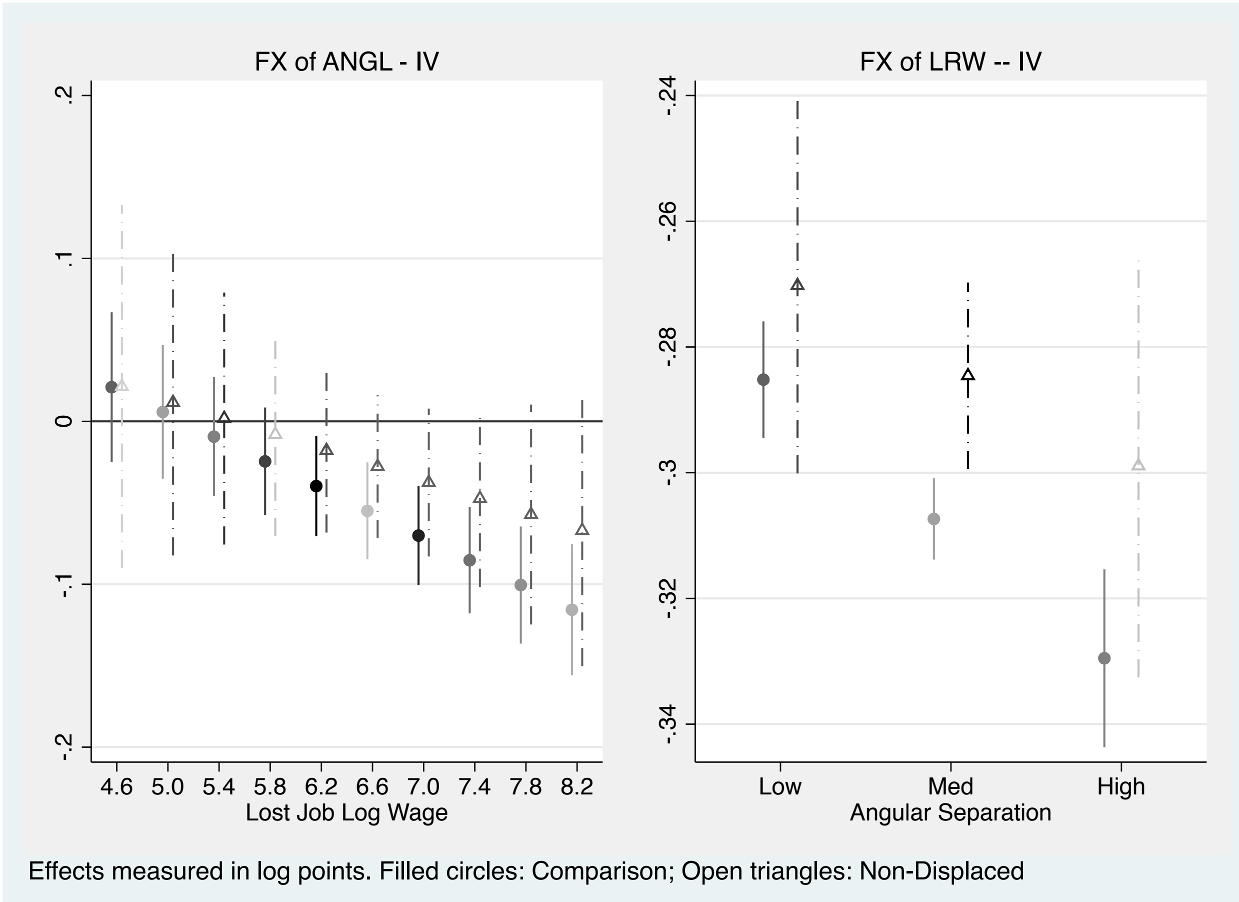

Figure F3: IV Predicted Effects, Wage-Interaction Model: Comparison and Non-Displaced Samples

Filled circles = Comparison, open triangles=Non-Displaced Sample. IV predicted effects and 90/95% confidence intervals from Equation 11 of a standard deviation increase in $ANGL$ and lost job real wage evaluated at medium (mean), low, and high (minus/plus 1 std. dev.) $ANGL$.

Notes

[1]We also ignore the issue of unobservable ability *within* occupations (Blien et al., 2019).

[2] Only in the ΔSKL models estimated on the Continuously Employed Sample are the estimated coefficients on the interaction terms negative and statistically significant, but even here, the IV Kleibergen-Paap F statistic falls from 42.34 to 10.41, and the standard error is twice as large.

G Empirical Results for Unadjusted Rank Measures

PCT and SKL were adjusted because the unadjusted measures reflect age, education, and industry composition of the occupation as well as rank. As this is not dispositive, for completeness this Appendix presents results using the unadjusted rank measures.

Occupational PCT and SKL Rankings Tables G1 and G2 show the 20 most and least-skilled occupations for the unadjusted measures. Given the positive correlations of 0.42 and 0.58 with the adjusted measures (see Table A8), it is not surprising to find substantial numbers of occupations in common in Tables A2 and A3.

Life Cycle Patterns The life cycle patterns of the unadjusted PCT and SKL measures, seen in Table G3, are similar to those of the adjusted measures.

Means of Key Variables Seen in Table G4, mean $ANGL$ generally declines in PCT and wage decile, and is inverse-U-shaped in SKL decile, not inconsistent with the patterns seen in the adjusted measures, and both patterns are consistent with the presence of skill-broadening among lower-rank job losers and task-specificity among higher-rank job losers. However, in contrast to the adjusted measures, unemployment duration and propensity to exhaust unemployment insurance benefits do not rise with PCT decile, which pattern presumably reflects confounding factors netted out from the adjusted measure. Standard errors appear in Table G8.

Means of Key Variables by Rank Decrease and Increase Seen in Table G5. As found for the adjusted measures, the mean value of $ANGL$ is higher among lower-rank job losers who find higher-rank jobs (col. 5) than those who move down in rank (col. 6), but higher among higher-rank job losers who find lower-rank jobs than among those who find higher-rank jobs (Table G6). Again, these patterns are consistent with the presence of career trajectory upgrading among lower-rank job losers and task specificity among higher-rank job losers. Standard errors appear in Table G9. The pattern is visualized in Figure G1. Again, random mobility is rejected (Table G7).

Regression Results The sign pattern on the estimated parsimonious regression coefficients for the unadjusted rank measures, seen in Table G10, and pattern of predicted effects, seen in Figure G2, are similar to those founding using adjusted rank measures, and are consistent with the presence of skill-broadening among lower-rank job losers and task specificity for higher-rank job losers. In contrast to the adjusted measures, exogeneity is rejected at the 5% level for ΔPCT, and only at the 10% level ΔSKL. Also in contrast to the adjusted measures, the estimated coefficients and standard errors for the Plant Closure Sample are close to those of the Displaced Sample. Tests of overidentification, seen in Table G11, are passed at the 5% level. For the Junior-Senior regressions (diagnostics in Table G12), exogeneity is generally rejected in both measures; the null hypothesis of Junior-Senior coefficient equality is rejected at the 0.4% level for PCT with a cutoff of 40, but only at the 9.1% level for a SKL cutoff of 20. The predicted effects, seen in the second and third rows of Figure G2, reinforce those obtained in the parsimonious model.

Summary The unadjusted rank measure analysis reinforces that using the adjusted measures.

Table G1: 20 Highest-and Lowest *PCT* Occupations, Unadjusted
With Changes for Occupation Switchers

		ΔPCT		
Occupation	*PCT*	Displ	Pl Clos	Cont'sly Emp
CEOs and Pub. Admin	99	-19	-21	-26
Lawyers	99	-30	-6	-25
N.e.c. engineers	98	-10	-7	-12
Mechanical engineers	98	-17	-22	-15
Electrical engineer	98	-16	-10	-16
Pharmacists	97	-31	-31	-27
Civil engineers	97	-16	-26	-16
Management analysts	96	-18	-19	-20
Industrial engineers	96	-16	-13	-16
Computer software developers	96	-13	-13	-15
Financial svs sales occs	96	-30	-38	-26
Mgrs, Mrktg, and kindred	95	-33	-37	-26
Human resources, labor relations mgrs	94	-22	-17	-18
Financial mgrs	94	-23	-23	-20
Mgrs, administrators, n.e.c.	92	-22	-22	-18
Architects	91	-43	-88	-18
Ops, systms rsrchrs, anlysts	91	-16	-17	-14
Ecnmsts, mkt, svy rsrchrs	91	-12	3	-9
Computer sci. and kindred	90	-14	-15	-12
Miners	89	-36	-28	-24
Teachers , n.e.c.	21	45	36	36
Textile sewing machine operators	20	12	11	19
Retail sales clerks	20	31	28	32
Nursing aides, orderlies, attendants	18	24	30	29
Bartenders	17	24	27	25
Hairdressers, cosmetologists	17	11	19	23
Packers, packagers by hand	17	18	14	24
File clerks	16	24	34	32
Janitors	15	29	36	30
Vehicle washers, equipment cleaners	14	31	30	30
Gardeners, groundskeepers	13	29	33	32
Cooks, variously defined	11	21	19	29
Farm workers	10	32	32	30
Waiter/waitress	8	28	29	28
Housekeepers and kindred	7	21	21	25
Stock handlers	7	38	29	37
Cashiers	4	31	28	40
Door-to-door, street sales	3	46	31	47
Misc food prep workers	2	28	22	25
Child care workers	1	23	33	39

This table lists the top- and bottom-20 *LPCT* 3-digit 1990 IPUMS occupations (Equation 1). Also reported are mean changes in *PCT* between the lost/last and current job.

Table G2: 20 Highest-and Lowest SKL Occupations, Unadjusted
With Changes for Occupation Switchers

			Δ SKL	
Occupation	SKL	Displ	Pl Clos	Cont'sly Emp
Architects	0.799	-0.745	-1.210	-0.497
Ops, systms rsrchrs, anlysts	0.755	-0.476	-0.308	-0.408
Lawyers	0.720	-0.555	-0.376	-0.410
Writers, authors	0.661	-0.303	-0.200	-0.441
Industrial engineers	0.648	-0.313	-0.329	-0.334
Clergy, religious workers	0.645	-0.240	-0.223	-0.324
Civil engineers	0.622	-0.278	-0.537	-0.238
Electrical engineer	0.600	-0.186	-0.152	-0.226
N.e.c. engineers	0.575	-0.095	-0.061	-0.118
Ecnmsts, mkt, svy rsrchrs	0.552	-0.220	0.011	-0.192
Mechanical engineers	0.543	-0.194	-0.218	-0.127
Computer software developers	0.523	-0.173	-0.157	-0.192
Human resources, labor relations mgrs	0.523	-0.363	-0.397	-0.263
Accountants, auditors	0.501	-0.304	-0.270	-0.320
Insurance underwriters	0.500	-0.302	-0.282	-0.410
Editors, reporters	0.490	-0.295	-0.306	-0.201
Mgrs in education, related fields	0.478	-0.328	-0.376	-0.225
Technical writers	0.462	-0.312	-0.355	-0.168
Financial mgrs	0.460	-0.208	-0.221	-0.216
Mgrs of medicine, health occs	0.446	-0.335	-0.413	-0.221
Typists	-0.355	0.343	0.204	0.333
Prod'n checkers, inspectors	-0.390	0.215	0.155	0.293
Machine operators, n.e.c.	-0.396	0.141	0.128	0.175
Assemblers of electrical equipment	-0.396	0.164	0.119	0.238
Grinders and kindred	-0.406	0.151	0.232	0.206
Cashiers	-0.410	0.174	0.127	0.328
Waiter/waitress	-0.417	0.257	0.262	0.321
Slicing, cutting machine operators	-0.427	0.201	0.220	0.117
Vehicle washers, equipment cleaners	-0.450	0.254	0.254	0.280
Freight, stock, materials handlers	-0.468	0.254	0.251	0.238
Janitors	-0.468	0.344	0.368	0.350
Misc food prep workers	-0.492	0.251	0.195	0.258
Housekeepers and kindred	-0.492	0.194	0.186	0.239
Telephone operators	-0.507	0.514	0.449	0.519
Laborers outside construction	-0.517	0.320	0.361	0.298
Nursing aides, orderlies, attendants	-0.541	0.410	0.374	0.447
Textile sewing machine operators	-0.578	0.186	0.167	0.233
Packers, packagers by hand	-0.612	0.286	0.210	0.280
Stock handlers	-0.627	0.400	0.264	0.490
Packers, fillers, wrappers	-0.647	0.290	0.276	0.261

This table lists the top- and bottom-20 $LSKL$ 3-digit 1990 IPUMS occupations (Equation 2). Also reported are mean changes in SKL between the lost/last and current job.

Table G3: Life Cycle Pattern of $LPCT$ and $LSKL$: Descriptive Regressions, Unadjusted Measures

	Dep. Var = $LPCT$			Dep. Var = $LSKL$		
	(1)	(2)	(3)	(4)	(5)	(6)
	Displ	Closure	CE	Displ	Closure	CE
Tenure 1-3 Years	2.4794	3.3113		0.0368	0.0468	
	(0.7165)	(0.9370)		(0.0091)	(0.0110)	
Tenure 3-10 Years	4.4418	5.8036		0.0515	0.0591	
	(1.0092)	(1.3957)		(0.0129)	(0.0155)	
Tenure 11-20 Years	5.7654	5.7873		0.0550	0.0448	
	(1.2097)	(1.7046)		(0.0153)	(0.0192)	
Tenure 20+ Years	6.2128	7.2967		0.0625	0.0532	
	(1.2152)	(1.8973)		(0.0138)	(0.0201)	
Age 20-24	-10.2054	-11.5431	-10.9783	-0.1035	-0.0970	-0.0993
	(1.5291)	(2.2323)	(1.3430)	(0.0171)	(0.0253)	(0.0117)
Age 25-34	-3.1497	-3.1756	-2.7821	-0.0230	-0.0195	-0.0223
	(0.7365)	(0.9936)	(0.4760)	(0.0079)	(0.0113)	(0.0039)
Age 45-54	0.0892	-0.5869	-0.1435	-0.0057	-0.0169	-0.0029
	(0.6461)	(0.8611)	(0.2968)	(0.0065)	(0.0088)	(0.0028)
Age 55-64	-0.8160	-3.1427	-1.7188	-0.0079	-0.0386	-0.0138
	(0.9458)	(1.3411)	(0.5653)	(0.0093)	(0.0137)	(0.0054)
Female	-8.4169	-8.1484	-9.1289	-0.1073	-0.1025	-0.1003
	(2.2007)	(2.2800)	(2.2512)	(0.0241)	(0.0254)	(0.0231)
Black	-5.9006	-5.8652	-7.9042	-0.0940	-0.0981	-0.1063
	(1.0813)	(1.6194)	(1.2702)	(0.0119)	(0.0182)	(0.0147)
Hispanic	-5.7109	-5.9853	-7.0291	-0.0687	-0.0830	-0.0701
	(0.9571)	(1.1208)	(0.9049)	(0.0102)	(0.0130)	(0.0074)
Other race	-0.0875	-2.5695	-4.2136	-0.0089	-0.0184	-0.0492
	(1.8360)	(2.0887)	(1.5105)	(0.0174)	(0.0185)	(0.0126)
Educ: Dropout	-6.5480	-6.7643	-8.3763	-0.0954	-0.1018	-0.1115
	(1.4431)	(1.9239)	(1.5393)	(0.0185)	(0.0224)	(0.0159)
Educ: Assoc Deg	9.4223	9.6172	11.6161	0.1494	0.1516	0.1640
	(1.4948)	(1.7262)	(2.1885)	(0.0196)	(0.0213)	(0.0251)
Educ: Some Coll	5.4682	5.7937	6.3262	0.0960	0.1054	0.1063
	(1.1544)	(1.3884)	(1.1860)	(0.0134)	(0.0166)	(0.0131)
Educ: Coll Grad	21.9558	22.0364	24.2251	0.3424	0.3333	0.3705
	(3.0184)	(3.0260)	(2.5949)	(0.0382)	(0.0399)	(0.0348)
Constant	50.8808	49.6550	55.0151	-0.0658	-0.0755	-0.0222
	(2.9014)	(3.3360)	(2.6759)	(0.0412)	(0.0426)	(0.0374)
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17873	6778	2758722	17873	6778	2758722
R-Square	.212	.2055	.2309	.2782	.2647	.3079

Note: "CE" denotes the Continuously Employed Sample. This table shows regressions of $LPCT$ and $LSKL$ on a variety of covariates as a way of illustrating the life cycle patterns of both rank measures. Because the samples retain occupation non-switchers, the sample sizes are larger than those in the remainder of the paper. Omitted categories are as follow: Tenure, less than 1 year; Age, 35-44; Eduction, high school degree.

Table G4: Means of Key Variables, Unadjusted Rank Measures

				A. *PCT* Deciles				
		All Displaced					Occ Switchers	
Decile	Δ Occ	RANK	Δ$WAGE$	Wks Unem	Exh. UI	ANGL	Δ RANK	Δ$WAGE$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1	0.66	6.05	0.03	8.87	0.07	74.30	24.99	0.05
2	0.67	15.78	0.00	12.00	0.13	70.41	11.95	0.01
3	0.79	25.73	-0.01	12.43	0.13	69.87	8.80	0.01
4	0.69	35.15	-0.08	13.30	0.14	71.45	9.43	-0.10
5	0.70	45.99	-0.07	14.40	0.16	67.99	-4.40	-0.10
6	0.60	54.98	-0.05	12.43	0.14	70.70	-2.45	-0.08
7	0.67	65.31	-0.09	12.03	0.13	65.85	-11.08	-0.10
8	0.59	74.81	-0.10	13.16	0.14	69.53	-13.39	-0.14
9	0.63	85.39	-0.12	11.60	0.12	61.43	-12.04	-0.20
10	0.64	94.96	-0.11	13.93	0.13	48.78	-13.49	-0.15
				B. *SKL* Deciles				
1	0.75	-0.57	-0.03	14.55	0.18	64.35	0.18	-0.04
2	0.75	-0.42	-0.03	13.85	0.15	69.62	0.13	-0.02
3	0.76	-0.30	-0.05	13.51	0.15	68.44	0.09	-0.06
4	0.63	-0.20	-0.01	10.84	0.10	74.00	0.06	-0.01
5	0.61	-0.10	-0.07	13.44	0.14	71.53	0.03	-0.10
6	0.69	-0.00	-0.11	12.90	0.15	72.25	-0.02	-0.14
7	0.58	0.14	-0.07	11.79	0.12	68.82	-0.09	-0.10
8	0.69	0.24	-0.10	12.75	0.12	63.94	-0.10	-0.13
9	0.63	0.37	-0.12	12.99	0.13	57.22	-0.12	-0.18
10	0.55	0.57	-0.07	12.39	0.12	52.07	-0.16	-0.11
				Wage Deciles				
1	0.74	5.84	0.20	10.25	0.10	71.04	0.21	0.21
2	0.74	6.20	0.06	13.52	0.16	71.97	0.05	0.05
3	0.70	6.39	0.02	10.91	0.12	72.98	0.00	0.00
4	0.69	6.55	-0.06	13.60	0.16	70.23	-0.10	-0.10
5	0.66	6.71	-0.09	13.23	0.16	70.86	-0.14	-0.14
6	0.65	6.86	-0.12	12.70	0.14	64.65	-0.18	-0.18
7	0.60	7.03	-0.16	13.78	0.15	60.74	-0.23	-0.23
8	0.58	7.22	-0.19	14.16	0.15	60.94	-0.26	-0.26
9	0.59	7.46	-0.23	12.51	0.12	54.84	-0.30	-0.30
10	0.59	7.89	-0.32	13.97	0.11	46.59	-0.38	-0.38

This Table contains means by (Part A) PCT, (Part B) SKL, and (Part C) real wage decile of (1) the fraction of displaced workers changing occupation, (2) the mean rank in the job, (3) the mean change in the real wage between the lost and current job, (4) weeks unemployed post-displacement, (5) the fraction exhausting their UI benefits, and, for occupation switchers, (6) mean values of $ANGL$, (7) the mean change in job rank (PCT, SKL or real wage,) and (8) the mean change in the real wage. The information in column (7) of Part C is redundant but is presented to preserve symmetry.

Table G5: Means by Rank Decrease and Increase, Unadjusted Rank Measures

	Wks Unem		Exh. UI		ANGL	
Decile	$\Delta R > 0$	$\Delta R < 0$	$\Delta R > 0$	$\Delta R < 0$	$\Delta R > 0$	$\Delta R < 0$
	(1)	(2)	(3)	(4)	(5)	(6)
A. *PCT* Deciles						
1	9.76	9.05	0.08	0.05	75.51	63.24
2	12.96	13.82	0.12	0.24	72.88	65.67
3	12.62	12.70	0.14	0.13	72.58	61.36
4	13.20	17.65	0.14	0.21	76.51	70.31
5	15.23	15.37	0.17	0.17	71.15	65.46
6	13.30	13.41	0.16	0.18	68.22	75.46
7	12.04	13.72	0.12	0.15	50.90	78.23
8	12.39	15.22	0.14	0.17	57.01	75.46
9	13.00	12.54	0.10	0.14	38.37	72.45
10	12.29	15.98	0.08	0.16	32.65	55.13
B. *SKL* Deciles						
1	13.99	17.44	0.17	0.24	68.31	38.63
2	15.50	13.44	0.15	0.20	74.64	51.61
3	13.30	15.35	0.15	0.20	73.90	58.11
4	11.77	11.59	0.10	0.13	78.51	67.64
5	14.96	14.43	0.16	0.16	72.85	70.07
6	12.64	14.55	0.15	0.17	70.45	73.79
7	13.24	12.55	0.13	0.15	58.67	74.31
8	12.58	14.09	0.11	0.15	39.78	77.15
9	12.37	15.33	0.11	0.16	36.57	65.29
10	11.91	14.49	0.08	0.15	33.15	55.35
C. Wage Deciles						
1	9.57	11.73	0.08	0.13	71.77	69.37
2	12.39	14.80	0.14	0.19	71.03	73.02
3	9.31	12.56	0.09	0.16	71.58	74.28
4	10.33	16.06	0.12	0.19	66.40	72.68
5	9.87	15.42	0.10	0.20	66.22	73.22
6	9.70	14.87	0.10	0.16	62.25	66.10
7	10.09	15.64	0.10	0.18	54.62	63.17
8	11.06	15.84	0.11	0.17	52.60	64.62
9	9.34	14.19	0.07	0.15	47.74	57.88
10	10.64	14.98	0.09	0.12	39.08	48.50

This Table contains means by (Part A) PCT, (Part B) SKL, and (Part C) real wage decile of weeks unemployed (1,2), the fraction exhausting their UI benefits (3,4) and $ANGL$ (5,6) for those experiencing rising ($\Delta R > 0$) and declining ($\Delta R < 0$) job rank, where $R = PCT,\ SKL$, or the real wage. We see generally higher mean values of $ANGL$ at lower ranks for rank increases (col. 5) than rank decreases (col. 6), which is consistent with career trajectory upgrade. We also see higher mean values of $ANGL$ at higher ranks for rank decreases than rank increases, which is consistent with the importance of task specificity.

Table G6: Differences in Search and Skill Composition Change by Lost Job Rank Decile, Unadjusted Rank Measures, Displaced Worker Sample

	PCT			*SKL*			*LRW*		
Decile	Weeks Un	Exh UI	*ANGL*	Weeks Un	Exh UI	*ANGL*	Weeks Un	Exh UI	*ANGL*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1	-0.71	-0.02	-12.27	3.44	0.07	-29.67	2.17	0.04	-2.39
	(3.05)	(0.04)	(4.66)	(2.61)	(0.04)	(2.53)	(0.87)	(0.02)	(1.91)
2	0.86	0.12	-7.21	-2.05	0.04	-23.03	2.40	0.05	1.99
	(1.66)	(0.04)	(2.68)	(1.49)	(0.03)	(2.32)	(1.02)	(0.02)	(1.82)
3	0.08	-0.01	-11.22	2.05	0.05	-15.79	3.25	0.07	2.70
	(1.60)	(0.03)	(2.54)	(1.39)	(0.02)	(1.79)	(0.86)	(0.02)	(2.10)
4	4.45	0.07	-6.21	-0.18	0.03	-10.87	5.73	0.07	6.29
	(1.34)	(0.02)	(1.78)	(1.16)	(0.02)	(1.95)	(1.00)	(0.02)	(2.20)
5	0.15	0.00	-5.69	-0.53	0.00	-2.79	5.55	0.10	7.00
	(1.07)	(0.02)	(1.60)	(1.27)	(0.02)	(1.95)	(0.94)	(0.02)	(2.31)
6	0.11	0.02	7.25	1.91	0.02	3.34	5.17	0.06	3.85
	(1.23)	(0.02)	(1.95)	(1.09)	(0.02)	(1.83)	(0.98)	(0.02)	(2.49)
7	1.68	0.03	27.33	-0.69	0.02	15.64	5.55	0.07	8.54
	(1.28)	(0.02)	(2.05)	(1.21)	(0.02)	(1.93)	(1.03)	(0.02)	(2.52)
8	2.83	0.03	18.44	1.51	0.04	37.37	4.78	0.06	12.02
	(1.21)	(0.02)	(1.97)	(1.04)	(0.02)	(1.57)	(1.15)	(0.02)	(2.58)
9	-0.46	0.04	34.08	2.96	0.05	28.72	4.85	0.08	10.13
	(1.12)	(0.02)	(1.64)	(0.97)	(0.02)	(1.63)	(0.94)	(0.02)	(2.67)
10	3.69	0.08	22.47	2.58	0.07	22.20	4.34	0.03	9.42
	(1.31)	(0.02)	(1.86)	(1.80)	(0.03)	(1.59)	(1.23)	(0.02)	(2.87)

Differences in means of indicated variable between those declining in rank and rising in rank. Positive values indicate higher mean for those declining in rank. Standard errors in parentheses.

Table G7: Mean Skill Composition Change by Decile, Unadjusted Rank Measures: Actual versus Random Mobility

	PCT			*SKL*			*WAGE*		
Rank	Disp	Cont's	Random	Disp	Cont's	Random	Disp	Comp	Random
1	74.3	80.2	92.6	64.3	66.5	90.1	71.0	65.5	89.1
2	70.4	72.3	90.2	69.6	70.5	90.0	72.0	65.5	90.0
3	69.9	72.6	89.5	68.4	73.1	90.3	73.0	64.8	90.2
4	71.5	72.4	90.4	74.0	77.2	90.3	70.2	64.1	89.1
5	68.0	65.5	88.3	71.5	70.6	90.4	70.9	62.2	88.1
6	70.7	71.3	88.3	72.2	63.8	90.5	64.6	60.6	86.8
7	65.8	61.2	87.0	68.8	60.0	88.2	60.7	58.1	87.1
8	69.5	68.3	89.4	63.9	54.5	86.7	60.9	54.9	84.3
9	61.4	57.4	86.1	57.2	52.7	83.6	54.8	49.3	86.4
10	48.8	46.8	84.0	52.1	50.7	83.2	46.6	42.4	85.5

This Table contains mean values of $ANGL$ in the Displaced, Continuously Employed or Comparison Samples, and under random mobility, by decile rank.

Table G8: Standard Errors of Mean of Key Variables, Unadjusted Rank Measures

Decile	Δ Occ	RANK	$\Delta WAGE$	Wks Unem	Exh. UI	ANGL	Δ RANK	$\Delta WAGE$
				A. *PCT* Deciles				
		All Displaced					Occ Switchers	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1	0.02	0.11	0.03	0.64	0.01	1.42	1.42	0.04
2	0.01	0.10	0.02	0.51	0.01	1.14	1.00	0.02
3	0.01	0.07	0.02	0.60	0.01	1.04	1.06	0.02
4	0.01	0.05	0.01	0.44	0.01	0.83	0.81	0.02
5	0.01	0.06	0.01	0.43	0.01	0.79	0.80	0.01
6	0.01	0.07	0.01	0.43	0.01	0.94	0.99	0.02
7	0.01	0.06	0.02	0.49	0.01	1.08	1.14	0.02
8	0.01	0.06	0.01	0.43	0.01	1.01	0.85	0.01
9	0.01	0.07	0.01	0.37	0.01	0.93	0.75	0.02
10	0.01	0.05	0.01	0.41	0.01	0.88	0.81	0.02
				B. *SKL* Deciles				
1	0.01	0.00	0.02	0.70	0.01	1.11	0.01	0.02
2	0.01	0.00	0.02	0.59	0.01	1.00	0.01	0.02
3	0.01	0.00	0.01	0.53	0.01	0.91	0.01	0.02
4	0.01	0.00	0.02	0.45	0.01	1.00	0.01	0.02
5	0.01	0.00	0.01	0.47	0.01	0.98	0.01	0.02
6	0.01	0.00	0.02	0.45	0.01	0.92	0.00	0.02
7	0.01	0.00	0.01	0.41	0.01	1.01	0.01	0.02
8	0.01	0.00	0.01	0.41	0.01	0.91	0.00	0.01
9	0.01	0.00	0.01	0.36	0.01	0.91	0.00	0.02
10	0.01	0.00	0.01	0.45	0.01	1.00	0.01	0.02
				Wage Deciles				
1	0.01	0.00	0.01	0.38	0.01	0.86	0.01	0.01
2	0.01	0.00	0.01	0.51	0.01	0.91	0.01	0.01
3	0.01	0.00	0.01	0.43	0.01	1.04	0.01	0.01
4	0.01	0.00	0.01	0.52	0.01	1.07	0.01	0.01
5	0.01	0.00	0.01	0.49	0.01	1.08	0.01	0.01
6	0.01	0.00	0.01	0.51	0.01	1.19	0.01	0.01
7	0.01	0.00	0.01	0.56	0.01	1.16	0.01	0.01
8	0.01	0.00	0.01	0.60	0.01	1.26	0.02	0.02
9	0.01	0.00	0.01	0.49	0.01	1.26	0.02	0.02
10	0.01	0.01	0.02	0.55	0.01	1.19	0.02	0.02

See note to Table G4.

Table G9: Standard Error of Means by Rank Decrease and Increase, Unadjusted Rank Measures

	A. *PCT* Deciles					
	Wks Unem		Exh. UI		ANGL	
Decile	$\Delta R > 0$	$\Delta R < 0$	$\Delta R > 0$	$\Delta R < 0$	$\Delta R > 0$	$\Delta R < 0$
	(1)	(2)	(3)	(4)	(5)	(6)
1	0.89	2.92	0.01	0.04	1.48	4.42
2	0.77	1.47	0.01	0.04	1.27	2.36
3	0.77	1.41	0.01	0.02	1.16	2.26
4	0.65	1.17	0.01	0.02	1.00	1.48
5	0.76	0.76	0.01	0.01	1.14	1.11
6	0.96	0.77	0.02	0.01	1.55	1.18
7	0.94	0.87	0.02	0.01	1.63	1.25
8	0.99	0.70	0.02	0.01	1.55	1.22
9	0.94	0.61	0.02	0.01	1.24	1.07
10	1.14	0.65	0.02	0.01	1.55	1.03
	B. *SKL* Deciles					
1	0.83	2.48	0.01	0.04	1.17	2.25
2	0.83	1.23	0.01	0.03	1.08	2.05
3	0.72	1.20	0.01	0.02	1.12	1.39
4	0.71	0.92	0.01	0.02	1.36	1.41
5	0.86	0.93	0.02	0.02	1.37	1.39
6	0.74	0.80	0.01	0.01	1.30	1.29
7	1.00	0.67	0.02	0.01	1.42	1.31
8	0.81	0.65	0.01	0.01	1.17	1.05
9	0.76	0.60	0.02	0.01	1.21	1.09
10	1.64	0.75	0.02	0.01	1.13	1.11
	C. Wage Deciles					
1	0.44	0.76	0.01	0.01	1.01	1.62
2	0.67	0.76	0.01	0.01	1.24	1.33
3	0.55	0.66	0.01	0.01	1.54	1.43
4	0.67	0.74	0.01	0.01	1.73	1.35
5	0.65	0.68	0.01	0.01	1.91	1.30
6	0.67	0.72	0.01	0.01	2.00	1.49
7	0.70	0.76	0.01	0.01	2.11	1.38
8	0.83	0.80	0.02	0.01	2.07	1.54
9	0.69	0.64	0.01	0.01	2.20	1.51
10	1.04	0.64	0.02	0.01	2.53	1.34

See note to Table G5.

Table G10: ΔPCT and ΔSKL Regressions, Unadjusted Measures

	A. Δ *PCT* Models					
	Displaced		Plant Closure		Continuously Employed	
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
LPCT	-0.2684	-0.4969	-0.2600	-0.4168	-0.1872	-0.4874
	(0.0352)	(0.1264)	(0.0417)	(0.1564)	(0.0427)	(0.1096)
ANGL	0.3927	0.3100	0.3768	0.3685	0.4850	0.2776
	(0.0362)	(0.1125)	(0.0486)	(0.1365)	(0.0353)	(0.1087)
$\times$ *LPCT*/100	-0.8663	-0.4842	-0.8314	-0.5525	-0.9511	-0.4865
	(0.0543)	(0.1707)	(0.0749)	(0.2118)	(0.0526)	(0.1419)
Endog P-Val		.01385		.04031		.005108
Kleibergen-Paap F		73.79		45.43		54.20
	B. Δ *SKL* Models					
	OLS	IV	OLS	IV	OLS	IV
LSKL	0.0037	-0.1572	0.0239	-0.0536	0.0533	-0.3370
	(0.0361)	(0.1114)	(0.0405)	(0.1315)	(0.0332)	(0.0701)
ANGL	-0.0005	0.0005	-0.0004	0.0000	0.0001	0.0004
	(0.0001)	(0.0007)	(0.0002)	(0.0007)	(0.0002)	(0.0005)
$\times$ *LSKL*	-0.0115	-0.0092	-0.0121	-0.0110	-0.0123	-0.0060
	(0.0004)	(0.0019)	(0.0005)	(0.0021)	(0.0004)	(0.0012)
Tenure	Yes	Yes	Yes	Yes	No	No
Age	Yes	Yes	Yes	Yes	Yes	Yes
Education	Yes	Yes	Yes	Yes	Yes	Yes
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Displ Year Effects	Yes	Yes	Yes	Yes	No	No
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
Endog P-Val		.09527		.6359		6.18e-06
Kleibergen-Paap F		72.09		32.25		37.73
Observations	11774	11770	4400	4398	42120	41995

Table G11: Overidentification Diagnostics: Rank Change Regressions, Unadjusted Measures

	A. Continuously Employed Instruments					
	Displaced		Plant Closure		Cont's'ly Emp.	
	(1)	(2)	(3)	(4)	(5)	(6)
	ΔPCT	ΔSKL	ΔPCT	ΔSKL	ΔPCT	ΔSKL
$LPCT$	-0.5108	0.0003	-0.4155	0.0004	-0.4403	0.0002
	(0.1250)	(0.0004)	(0.1566)	(0.0004)	(0.0901)	(0.0002)
$LSKL$	6.5920	-0.1647	3.0193	-0.0615	2.3831	-0.3132
	(2.4765)	(0.1117)	(3.7773)	(0.1317)	(1.3763)	(0.0804)
$ANGL$	0.2865	0.0005	0.3650	0.0002	0.3021	0.0006
	(0.1118)	(0.0007)	(0.1369)	(0.0007)	(0.0864)	(0.0005)
$\times LPCT$	-0.4690		-0.5568		-0.5243	
	(0.1696)		(0.2121)		(0.1269)	
$\times LSKL$		-0.0091		-0.0109		-0.0069
		(0.0019)		(0.0021)		(0.0013)
Hansen J-Statistic	2.70	0.33	0.76	1.09	1.50	4.53
J p-value	0.1001	0.5658	0.3845	0.2974	0.2211	0.0332
	B. Comparison Instruments					
$LPCT$	-0.5147	0.0003	-0.3928	0.0004	-0.4403	0.0002
	(0.1285)	(0.0004)	(0.1642)	(0.0005)	(0.0901)	(0.0002)
$LSKL$	6.8683	-0.1436	3.2588	-0.0094	2.3831	-0.3132
	(2.4847)	(0.1132)	(3.8781)	(0.1378)	(1.3763)	(0.0804)
$ANGL$	0.2590	0.0003	0.3681	0.0002	0.3021	0.0006
	(0.1185)	(0.0007)	(0.1460)	(0.0007)	(0.0864)	(0.0005)
$\times LPCT$	-0.4738		-0.5964		-0.5243	
	(0.1754)		(0.2172)		(0.1269)	
$\times LSKL$		-0.0094		-0.0117		-0.0069
		(0.0019)		(0.0023)		(0.0013)
Hansen J-Statistic	0.05	2.58	0.02	1.12	1.50	4.53
J p-value	0.8268	0.1084	0.8848	0.2896	0.2211	0.0332

The J tests are carried out by augmenting the instruments to include the Non-Displaced sample mean of $ANGL$. Continuously Employed means serve as instruments for the Displaced and Plant Closure Samples, and Displaced Means serve as instruments for the Continuously Employed Sample.

Table G12: Diagnostic Tests of ΔPCT and ΔSKL Models, Junior-Senior Specification: Unadjusted Measures

				PCT Models						
JR	Displaced Sample					Plant Closure Sample				
Cut	Endog	IV: EQ	RMSE	OLS: EQ	RMSE	Endog	IV: EQ	RMSE	OLS: EQ	RMSE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1	0.102	0.043	22.606	0.008	21.956	0.053	0.037	22.316	0.016	21.664
2	0.111	0.000	22.522	0.000	21.904	0.045	0.000	22.233	0.000	21.572
3	0.040	0.003	22.626	0.004	21.914	0.051	0.001	22.310	0.001	21.589
4	0.044	0.004	22.720	0.001	21.915	0.052	0.024	22.291	0.006	21.618
5	0.092	0.310	22.770	0.005	21.893	0.143	0.068	22.406	0.000	21.540
6	0.020	0.035	22.968	0.194	21.942	0.096	0.001	22.717	0.032	21.601
7	0.003	0.098	23.154	0.638	21.972	0.007	0.045	23.259	0.814	21.715
8	0.003	0.027	23.280	0.684	21.971	0.012	0.017	23.567	0.745	21.706
9	0.031	0.233	22.939	0.156	21.960	0.057	0.039	23.647	0.784	21.710
				SKL Models						
1	0.010	0.154	0.252	0.494	0.246	0.169	0.359	0.248	0.137	0.247
2	0.003	0.091	0.252	0.865	0.246	0.079	0.214	0.247	0.396	0.247
3	0.034	0.409	0.250	0.502	0.246	0.019	0.886	0.247	0.882	0.247
4	0.017	0.374	0.250	0.309	0.246	0.004	0.923	0.246	0.695	0.247
5	0.041	0.445	0.249	0.251	0.246	0.013	0.770	0.247	0.782	0.247
6	0.000	0.557	0.250	0.081	0.246	0.008	0.741	0.248	0.169	0.247
7	0.001	0.504	0.251	0.279	0.246	0.018	0.803	0.246	0.019	0.246
8	0.078	0.047	0.252	0.000	0.246	0.656	0.620	0.248	0.001	0.246
9	0.037	0.155	0.252	0.019	0.246	0.644	0.483	0.248	0.002	0.246

Diagnostics for JR-SR rank change models (Equation 8). Endogeneity pvals: cols. 1, 6; JR-SR equality pvals (see Equation 9): 2, 4, 7, 9; root means square errors: cols. 3, 5, 8, 10.

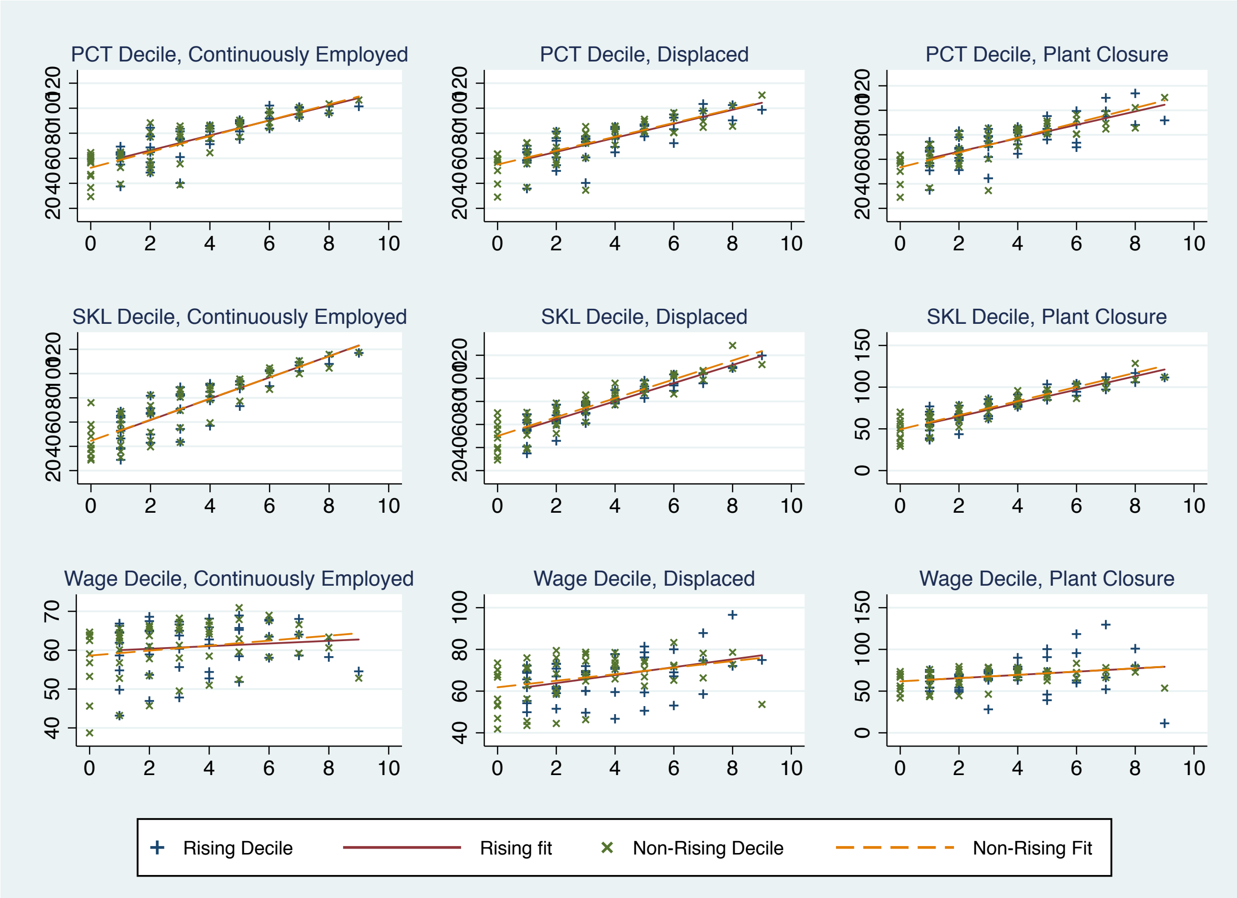

Figure G1: Unadjusted Rank Measures: Mean *ANGL* Conditional on Absolute Difference Between Lost/Last and Current Job Rank Decile, Rising (+) and Non-Rising (x) Shown Separately

This figure graphs the mean values of *ANGL* conditional on lost/last and current skill decile as a function of the absolute change in rank decile. A positive slope for upward moves in rank ("+") is evidence consistent with career trajectory upgrade, while a positive slope for downward moves and rank stayers ("x") is evidence consistent with task specificity.

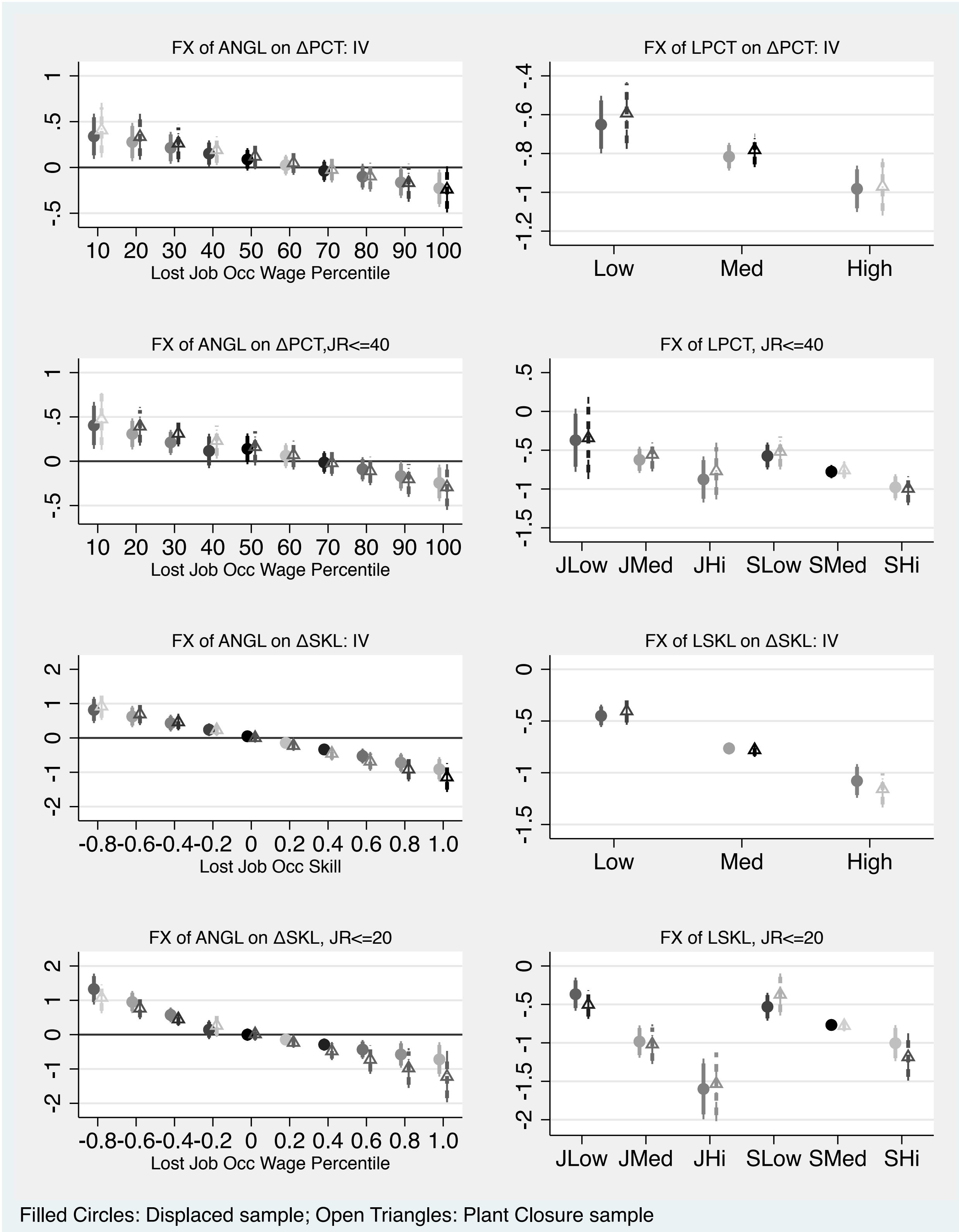

Figure G2: Rank Regression Predicted Effects, Unadjusted Rank Measures

Notes

[1]We also ignore the issue of unobservable ability *within* occupations (Blien et al., 2019).

[2] Only in the ΔSKL models estimated on the Continuously Employed Sample are the estimated coefficients on the interaction terms negative and statistically significant, but even here, the IV Kleibergen-Paap F statistic falls from 42.34 to 10.41, and the standard error is twice as large.

H Additional Empirical Results

This Appendix contains additional empirical results for completeness.

Specifications with "Cross" Interactions The ΔPCT models exclude an interaction between $ANGL$ and $LSKL$, and the ΔSKL models, between $ANGL$ and $LPCT$ because we view our rank measures as imperfect and as substitutes for one another. Appendix Table H1 shows that the "cross effects" are not statistically significant in IV estimation using the adjusted rank measures, and so are excluded on the grounds of efficiency. Estimates using the unadjusted measures are noisy and uninformative, perhaps because the unadjusted measures are highly correlated with one another. Absent an obvious way to integrate the two rank measures, we treat them separately, each as an imperfect measure of the true, underlying rank.

Temporal Stability All regression models include year dummy variables that net out any year-specific fluctuations in either the independent or dependent variables. However, concern could arise that the results are being driven by one or several years of data. Although causal analysis and precision are problematic on a year-to-year basis, it is useful to examine the predicted effects based on the partial correlations in the data. We re-estimate our rank and wage-interaction wage regressions using ordinary least squares, key coefficients reported in Tables H2 and H3, and plot the estimated effects of $ANGL$ evaluated at low, medium, and high rank (wages) in Figures H1 and H2. The predicted effects are stable for the ΔSKL measure. The estimated effects for ΔPCT regressions widen towards the middle years and then narrow somewhat. It does not appear that either set of results is being driven by just a few years of data. The predicted effects for wages are more variable, with some positive and negative spikes visible, especially for the Plant Closure Sample. However, the cell sizes are small, with 210 or fewer observations in the last three years. Given the relatively small sample sizes, we think that it is reasonable to present results that pool the data over the entire period.

Occupation Fixed Effects Occupation dummy variables would wash out the effect of $LPCT$ and $LSKL$ and our instruments, which vary only at the occupation level. However, the key hypothesis of our paper is that changes in skill composition are particularly costly for workers who lose more highly ranked jobs. We can therefore estimate a model that includes occupation dummy variables, dropping lost job rank in the rank change models, and estimate using OLS. The key estimated coefficients from these regressions are seen in Appendix Table H7. The key results are that the estimated coefficients on $ANGL$ are positive, and those on in the interaction between $ANGL$ and lost job rank, negative, just as found in the models presented in the text.

Assymetry That career trajectory upgrading is more apparent in rank changes than in wage changes implies that upward moves in rank translate less readily into wage increases than downward moves translate into wage decreases. This impression is supported by a descriptive exercise in which wage changes are regressed on rank changes where positive and negative changes are permitted to have different effects, seen in Table H8. See Section 7.2 for more discussion.

Table H1: ΔPCT and ΔSKL Regressions with "Cross" Interactions: IV Estimates

	Displaced				Plant Closure			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	PCT CE	PCT CO	SKL CE	SKL CO	PCT CO	PCT NC	SKL CO	SKL NC
$LPCT$	-0.6326	-0.6297	-0.0005	-0.0001	-0.7409	-0.5722	-0.0007	0.0007
	(0.0771)	(0.0756)	(0.0008)	(0.0008)	(0.0995)	(0.1543)	(0.0009)	(0.0009)
$LSKL$	4.5534	9.2691	-0.1645	-0.1498	-11.4755	17.4842	-0.0497	-0.2157
	(14.6015)	(15.3180)	(0.1226)	(0.1214)	(21.9361)	(31.5668)	(0.1399)	(0.1886)
$ANGL$	0.2062	0.1986	-0.0003	-0.0000	0.1043	0.3086	-0.0007	0.0005
	(0.0744)	(0.0739)	(0.0010)	(0.0010)	(0.0976)	(0.1610)	(0.0010)	(0.0010)
$\times LPCT/100$	-0.3623	-0.3682	0.0009	0.0003	-0.2404	-0.4581	0.0009	-0.0011
	(0.1090)	(0.1091)	(0.0012)	(0.0012)	(0.1304)	(0.2086)	(0.0013)	(0.0013)
$\times LSKL$	0.0462	-0.0264	-0.0085	-0.0087	0.2997	-0.1481	-0.0104	-0.0078
	(0.2180)	(0.2279)	(0.0019)	(0.0019)	(0.3310)	(0.4799)	(0.0022)	(0.0029)
Endog Chi-Sq	5.754	4.713	8.429	5.974	6.022	5.968	2.249	2.31
Endog P-Val	.1242	.1941	.03793	.1129	.1105	.1132	.5223	.5106
Kleibergen-Paap F	47	43	47	43	16	8.4	16	8.4
Observations	11770	11774	11770	11774	4400	4396	4400	4396
R-Square	.4523	.4562	.4675	.475	.4527	.451	.4936	.4884

Instruments: CE=Continuously Employed Comparison Sample; CO = Comparison Sample; NC = Non-Plant Closure Displaced Sample. Standard errors clustered on 1990 occupation are shown in parentheses.

Table H2: *PCT* Models: Estimated OLS Coefficients by Survey Year

	Displaced				Plant Closure			
	ANGL	ANGL x RANK	RANK	N	ANGL	ANGL x RANK	RANK	N
1994	0.1379	-0.3152	-0.6660	1,151	0.0080	-0.2316	-0.7263	452
	(0.0881)	(0.1206)	(0.0912)		(0.1238)	(0.1670)	(0.1424)	
1996	0.2051	-0.4447	-0.6010	967	0.0284	-0.1815	-0.8712	347
	(0.0765)	(0.1112)	(0.0827)		(0.1086)	(0.1551)	(0.1254)	
1998	0.0136	-0.1871	-0.7793	955	0.0906	-0.2911	-0.7026	389
	(0.0768)	(0.1103)	(0.0840)		(0.1391)	(0.1874)	(0.1413)	
2000	0.1411	-0.3381	-0.6312	874	0.2611	-0.4453	-0.5460	399
	(0.1032)	(0.1485)	(0.1174)		(0.1488)	(0.2072)	(0.1697)	
2002	0.1099	-0.3786	-0.6636	1,127	0.0525	-0.3032	-0.7005	475
	(0.0781)	(0.1036)	(0.0818)		(0.1157)	(0.1545)	(0.1307)	
2004	0.1454	-0.4771	-0.5989	1,273	0.0675	-0.3519	-0.7313	509
	(0.0716)	(0.1097)	(0.0736)		(0.1103)	(0.1533)	(0.1144)	
2006	0.2180	-0.6286	-0.4952	880	0.0995	-0.4846	-0.5993	396
	(0.0724)	(0.1030)	(0.0787)		(0.1106)	(0.1623)	(0.1237)	
2008	0.3559	-0.7232	-0.4209	833	0.3053	-0.6195	-0.5333	317
	(0.0718)	(0.1065)	(0.0798)		(0.0955)	(0.1363)	(0.0940)	
2010	0.2563	-0.6341	-0.4904	1,010	0.0969	-0.4071	-0.7037	296
	(0.0726)	(0.1085)	(0.0757)		(0.1039)	(0.1611)	(0.1199)	
2012	0.2728	-0.6862	-0.4169	951	0.1603	-0.6449	-0.5326	278
	(0.0645)	(0.0985)	(0.0623)		(0.1226)	(0.1719)	(0.1032)	
2014	0.2112	-0.4879	-0.5850	667	0.0902	-0.3428	-0.5880	210
	(0.0818)	(0.1227)	(0.0934)		(0.1276)	(0.1739)	(0.1218)	
2016	0.2353	-0.5488	-0.5053	554	0.2639	-0.5738	-0.4840	171
	(0.0810)	(0.1348)	(0.0831)		(0.1264)	(0.1711)	(0.1471)	
2018	0.1840	-0.4746	-0.5800	532	0.1069	-0.3937	-0.6257	161
	(0.0814)	(0.1100)	(0.0806)		(0.1655)	(0.2212)	(0.1552)	

Table H3: SKL Models: Estimated OLS Coefficients by Survey Year

	Displaced				Plant Closure			
	ANGL	ANGL x RANK	RANK	N	ANGL	ANGL x RANK	RANK	N
1994	-0.0001	-0.0111	-0.0318	1,151	-0.0002	-0.0115	-0.0286	452
	(0.0002)	(0.0008)	(0.0629)		(0.0003)	(0.0012)	(0.0871)	
1996	-0.0001	-0.0117	0.0321	967	0.0001	-0.0130	0.1028	347
	(0.0002)	(0.0009)	(0.0640)		(0.0003)	(0.0013)	(0.0947)	
1998	-0.0004	-0.0103	-0.0514	955	-0.0001	-0.0109	0.0018	389
	(0.0002)	(0.0008)	(0.0678)		(0.0003)	(0.0013)	(0.1006)	
2000	-0.0004	-0.0113	0.0282	874	-0.0003	-0.0116	0.0509	399
	(0.0002)	(0.0009)	(0.0639)		(0.0002)	(0.0010)	(0.0857)	
2002	-0.0003	-0.0113	0.0526	1,127	-0.0004	-0.0123	0.1424	475
	(0.0002)	(0.0007)	(0.0579)		(0.0002)	(0.0012)	(0.0838)	
2004	-0.0001	-0.0120	0.0389	1,273	-0.0001	-0.0122	0.0139	509
	(0.0001)	(0.0006)	(0.0377)		(0.0002)	(0.0009)	(0.0516)	
2006	-0.0005	-0.0089	-0.1008	880	-0.0006	-0.0087	-0.1357	396
	(0.0002)	(0.0006)	(0.0427)		(0.0002)	(0.0009)	(0.0595)	
2008	-0.0004	-0.0109	0.0009	833	-0.0005	-0.0124	0.1535	317
	(0.0001)	(0.0007)	(0.0450)		(0.0002)	(0.0012)	(0.0783)	
2010	-0.0003	-0.0114	-0.0012	1,010	-0.0004	-0.0125	0.0763	296
	(0.0001)	(0.0009)	(0.0542)		(0.0002)	(0.0015)	(0.1011)	
2012	-0.0002	-0.0124	0.0583	951	-0.0001	-0.0116	-0.0187	278
	(0.0001)	(0.0007)	(0.0464)		(0.0002)	(0.0012)	(0.0709)	
2014	0.0001	-0.0111	0.0173	667	0.0004	-0.0114	0.0382	210
	(0.0002)	(0.0006)	(0.0573)		(0.0003)	(0.0012)	(0.0985)	
2016	-0.0003	-0.0108	0.0440	554	-0.0007	-0.0118	0.1656	171
	(0.0002)	(0.0009)	(0.0717)		(0.0004)	(0.0021)	(0.1487)	
2018	-0.0004	-0.0111	-0.0187	532	-0.0007	-0.0115	0.0049	161
	(0.0002)	(0.0008)	(0.0639)		(0.0003)	(0.0019)	(0.1437)	

Table H4: Wage Models: Estimated OLS Coefficients by Survey Year

	ANGL	ANGL x RANK	RANK	N	ANGL	ANGL x RANK	RANK	N
1994	0.0074	-0.0012	-0.4710	787	0.0043	-0.0008	-0.4538	310
	(0.0045)	(0.0007)	(0.0747)		(0.0090)	(0.0014)	(0.1286)	
1996	0.0158	-0.0026	-0.3030	834	0.0046	-0.0009	-0.5052	290
	(0.0057)	(0.0009)	(0.0781)		(0.0102)	(0.0016)	(0.1312)	
1998	0.0113	-0.0020	-0.2823	816	0.0093	-0.0017	-0.1892	326
	(0.0041)	(0.0006)	(0.0553)		(0.0061)	(0.0009)	(0.0828)	
2000	0.0067	-0.0011	-0.3714	744	0.0095	-0.0016	-0.2918	334
	(0.0039)	(0.0006)	(0.0496)		(0.0095)	(0.0015)	(0.1043)	
2002	0.0079	-0.0014	-0.3537	944	0.0086	-0.0014	-0.3415	386
	(0.0052)	(0.0008)	(0.0695)		(0.0126)	(0.0019)	(0.1360)	
2004	0.0099	-0.0017	-0.2807	1,062	0.0058	-0.0013	-0.2928	415
	(0.0046)	(0.0007)	(0.0492)		(0.0067)	(0.0010)	(0.0780)	
2006	0.0107	-0.0018	-0.3074	728	0.0039	-0.0009	-0.4279	314
	(0.0050)	(0.0008)	(0.0597)		(0.0060)	(0.0009)	(0.0943)	
2008	0.0012	-0.0003	-0.3891	690	-0.0011	0.0002	-0.3005	267
	(0.0060)	(0.0009)	(0.0711)		(0.0082)	(0.0012)	(0.0911)	
2010	0.0128	-0.0022	-0.3434	831	-0.0012	-0.0001	-0.5299	238
	(0.0056)	(0.0008)	(0.0536)		(0.0159)	(0.0024)	(0.1809)	
2012	0.0201	-0.0033	-0.2031	748	0.0274	-0.0044	-0.0403	215
	(0.0056)	(0.0008)	(0.0654)		(0.0129)	(0.0020)	(0.1374)	
2014	-0.0017	0.0001	-0.5135	526	0.0020	-0.0002	-0.4037	158
	(0.0073)	(0.0011)	(0.0779)		(0.0106)	(0.0016)	(0.1281)	
2016	0.0181	-0.0028	-0.3900	446	0.0143	-0.0019	-0.5434	138
	(0.0065)	(0.0010)	(0.0805)		(0.0104)	(0.0016)	(0.1391)	
2018	0.0195	-0.0032	-0.2476	433	0.0339	-0.0054	-0.1354	130
	(0.0074)	(0.0011)	(0.0729)		(0.0084)	(0.0013)	(0.1097)	

Table H5: Unadjusted *PCT* Models: Estimated OLS Coefficients by Survey Year

	Displaced				Plant Closure			
	ANGL	ANGL x RANK	RANK	N	ANGL	ANGL x RANK	RANK	N
1994	0.4520	-0.8991	-0.1928	1,151	0.3546	-0.7502	-0.3230	452
	(0.0620)	(0.1032)	(0.0795)		(0.0794)	(0.1322)	(0.1245)	
1996	0.4171	-0.8645	-0.2488	967	0.4339	-0.9132	-0.2790	347
	(0.0726)	(0.1106)	(0.0886)		(0.0935)	(0.1504)	(0.1197)	
1998	0.2950	-0.6927	-0.4243	955	0.3193	-0.6720	-0.3397	389
	(0.0566)	(0.0977)	(0.0851)		(0.0859)	(0.1590)	(0.1230)	
2000	0.4099	-0.8785	-0.2722	874	0.4523	-0.8996	-0.1588	399
	(0.0613)	(0.1065)	(0.0910)		(0.0937)	(0.1651)	(0.1450)	
2002	0.3145	-0.7482	-0.3290	1,127	0.3723	-0.8258	-0.2579	475
	(0.0653)	(0.1010)	(0.0708)		(0.0949)	(0.1407)	(0.1328)	
2004	0.4318	-0.9298	-0.2835	1,273	0.4129	-0.9238	-0.2589	509
	(0.0492)	(0.0777)	(0.0643)		(0.0689)	(0.1009)	(0.1055)	
2006	0.2373	-0.6603	-0.4064	880	0.1453	-0.5051	-0.4588	396
	(0.0597)	(0.0879)	(0.0683)		(0.0831)	(0.1227)	(0.0916)	
2008	0.3691	-0.8431	-0.3314	833	0.3457	-0.7844	-0.3746	317
	(0.0535)	(0.0752)	(0.0680)		(0.0870)	(0.1240)	(0.1099)	
2010	0.3997	-0.9242	-0.2259	1,010	0.3397	-0.7681	-0.2784	296
	(0.0626)	(0.0960)	(0.0699)		(0.0999)	(0.1542)	(0.1183)	
2012	0.4254	-0.9250	-0.2387	951	0.3339	-0.8057	-0.4687	278
	(0.0567)	(0.0773)	(0.0686)		(0.0891)	(0.1232)	(0.1308)	
2014	0.4751	-0.9502	-0.3149	667	0.5212	-1.0147	-0.1733	210
	(0.0737)	(0.1055)	(0.0779)		(0.1397)	(0.2109)	(0.1289)	
2016	0.4294	-0.9399	-0.1687	554	0.4338	-1.0067	-0.1218	171
	(0.0574)	(0.0839)	(0.0614)		(0.1152)	(0.1858)	(0.1681)	
2018	0.3682	-0.8506	-0.2718	532	0.1899	-0.6479	-0.2041	161
	(0.0867)	(0.1144)	(0.0712)		(0.1644)	(0.2264)	(0.1796)	

Table H6: Unadjusted SKL Models: Estimated OLS Coefficients by Survey Year

	Displaced				Plant Closure			
	ANGL	ANGL x RANK	RANK	N	ANGL	ANGL x RANK	RANK	N
1994	-0.0003	-0.0115	-0.0738	1,151	-0.0003	-0.0121	-0.0373	452
	(0.0003)	(0.0008)	(0.0686)		(0.0005)	(0.0012)	(0.1052)	
1996	-0.0002	-0.0123	0.0318	967	-0.0000	-0.0137	0.1326	347
	(0.0003)	(0.0010)	(0.0726)		(0.0005)	(0.0013)	(0.1028)	
1998	-0.0007	-0.0110	-0.0537	955	-0.0002	-0.0113	-0.0645	389
	(0.0003)	(0.0008)	(0.0739)		(0.0005)	(0.0013)	(0.1095)	
2000	-0.0008	-0.0119	0.0556	874	-0.0006	-0.0125	0.0367	399
	(0.0003)	(0.0009)	(0.0669)		(0.0004)	(0.0010)	(0.0856)	
2002	-0.0006	-0.0115	0.0153	1,127	-0.0007	-0.0125	0.1162	475
	(0.0003)	(0.0007)	(0.0710)		(0.0004)	(0.0012)	(0.1031)	
2004	-0.0002	-0.0121	0.0587	1,273	-0.0003	-0.0126	-0.0373	509
	(0.0002)	(0.0006)	(0.0487)		(0.0003)	(0.0009)	(0.0634)	
2006	-0.0009	-0.0091	-0.0856	880	-0.0010	-0.0091	-0.1533	396
	(0.0003)	(0.0006)	(0.0628)		(0.0003)	(0.0009)	(0.0813)	
2008	-0.0006	-0.0109	0.0192	833	-0.0007	-0.0127	0.2042	317
	(0.0002)	(0.0006)	(0.0488)		(0.0004)	(0.0011)	(0.0846)	
2010	-0.0005	-0.0117	0.0037	1,010	-0.0005	-0.0130	0.0583	296
	(0.0002)	(0.0009)	(0.0676)		(0.0003)	(0.0015)	(0.1159)	
2012	-0.0002	-0.0129	0.0574	951	-0.0002	-0.0119	0.1038	278
	(0.0002)	(0.0007)	(0.0641)		(0.0004)	(0.0012)	(0.0897)	
2014	0.0001	-0.0118	0.0960	667	0.0006	-0.0117	0.0198	210
	(0.0003)	(0.0007)	(0.0813)		(0.0005)	(0.0011)	(0.1476)	
2016	-0.0004	-0.0114	0.0090	554	-0.0012	-0.0128	0.2250	171
	(0.0003)	(0.0008)	(0.0783)		(0.0006)	(0.0020)	(0.1745)	
2018	-0.0006	-0.0112	-0.0764	532	-0.0011	-0.0117	0.0005	161
	(0.0003)	(0.0008)	(0.0744)		(0.0006)	(0.0020)	(0.1831)	

Table H7: Rank and Earnings Regressions: Occupation Fixed Effects Estimates

	A. ΔPCT Models					
	Displaced		Plant Closure		Comparison	
	(1)	(2)	(3)	(4)	(5)	(6)
	Adj	Unadj	Adj	Unadj	Adj	Unadj
ANGL	0.2141	0.4165	0.1409	0.3778	0.2929	0.5296
	(0.0509)	(0.0361)	(0.0691)	(0.0483)	(0.0416)	(0.0374)
× *LRANK*	-0.5325	-0.9266	-0.4308	-0.8530	-0.6056	-1.0487
	(0.0732)	(0.0503)	(0.0980)	(0.0705)	(0.0629)	(0.0517)
Observations	11774	11774	4400	4400	42120	42120
	B. ΔSKL Models					
	(1)	(2)	(3)	(4)	(5)	(6)
ANGL	-0.0003	-0.0005	-0.0003	-0.0005	0.0000	-0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0002)
× *LRANK*	-0.0117	-0.0120	-0.0119	-0.0122	-0.0126	-0.0128
	(0.0003)	(0.0004)	(0.0005)	(0.0005)	(0.0003)	(0.0003)
Observations	11774	11774	4400	4400	42120	42120
	C. ΔLRW Models					
	(1)	(2)	(3)	(4)	(5)	(6)
ANGL	0.0103	0.0103	0.0073	0.0073	0.0077	0.0077
	(0.0017)	(0.0017)	(0.0030)	(0.0030)	(0.0007)	(0.0007)
× *LRW*	-0.0018	-0.0018	-0.0013	-0.0013	-0.0012	-0.0012
	(0.0003)	(0.0003)	(0.0005)	(0.0005)	(0.0001)	(0.0001)
Observations	9589	9589	3521	3521	196829	196829

Selected coefficients from regressions that control for 1990 occupation. ΔPCT and ΔSKL models drop $LPCT$ and $LSKL$, which vary only at the occupation level. Estimation is carried out using OLS because IV estimates use occupation-level means as instruments, which are washed out by the occupation dummies. There are no adjusted/unadjusted earnings models; the regressions are repeated for the sake of presentation.

Table H8: Asymmetry, Part I: Wage Changes and Rank Changes

	Displaced	Plant Closure	Comparison
Δ *PCT*, Positive	0.0001	-0.0002	0.0000
	(0.0003)	(0.0005)	(0.0003)
Δ *PCT*, Negative	0.0020	0.0020	0.0008
	(0.0002)	(0.0003)	(0.0001)
Δ *SKL*, Positive	0.0146	0.0652	0.0452
	(0.0424)	(0.0656)	(0.0299)
Δ *SKL*, Negative	0.3980	0.2970	0.2948
	(0.0461)	(0.0659)	(0.0343)

This table contains OLS estimates of the change in the real wage on the change in rank between the lost/last job and the current job, where positive and negative rank changes are permitted to enter with different coefficients. All models include the same X_i controls (tenure, age, education, demographics, and year) as in the main models. These regressions are purely descriptive, and show that positive changes in rank translate into wage changes at a lower rate than do negative changes.

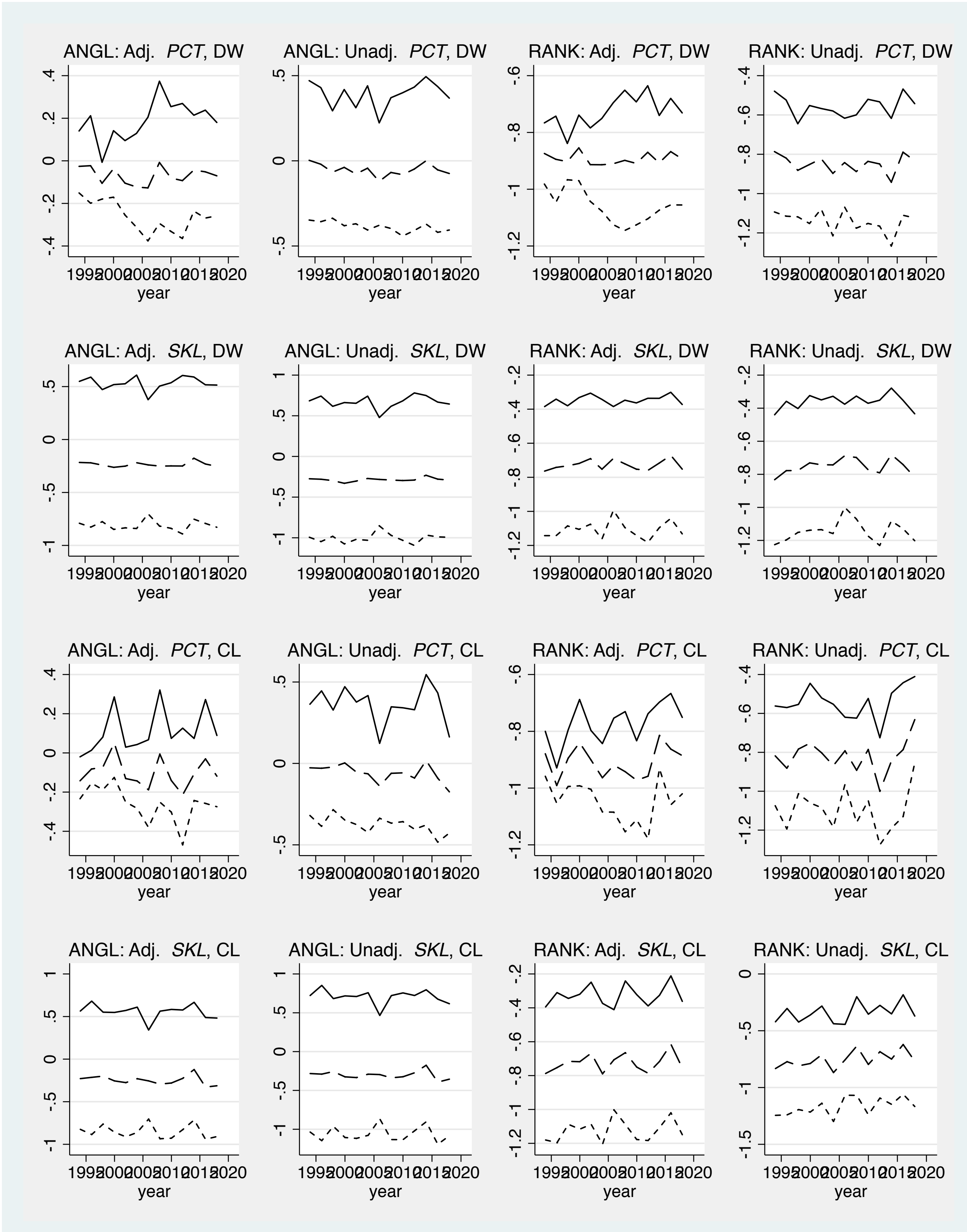

Figure H1: Rank Regressions OLS Predicted Effects by Year

ANGL effects evaluated at *PCT*=10, 50, 80; Adjusted (unadjusted) *SKL*=levels -0.3, 0.1, 0.4 (-0.6, 0.2 0.8); *RANK* effects evaluated at low, medium, and high *ANGL*.

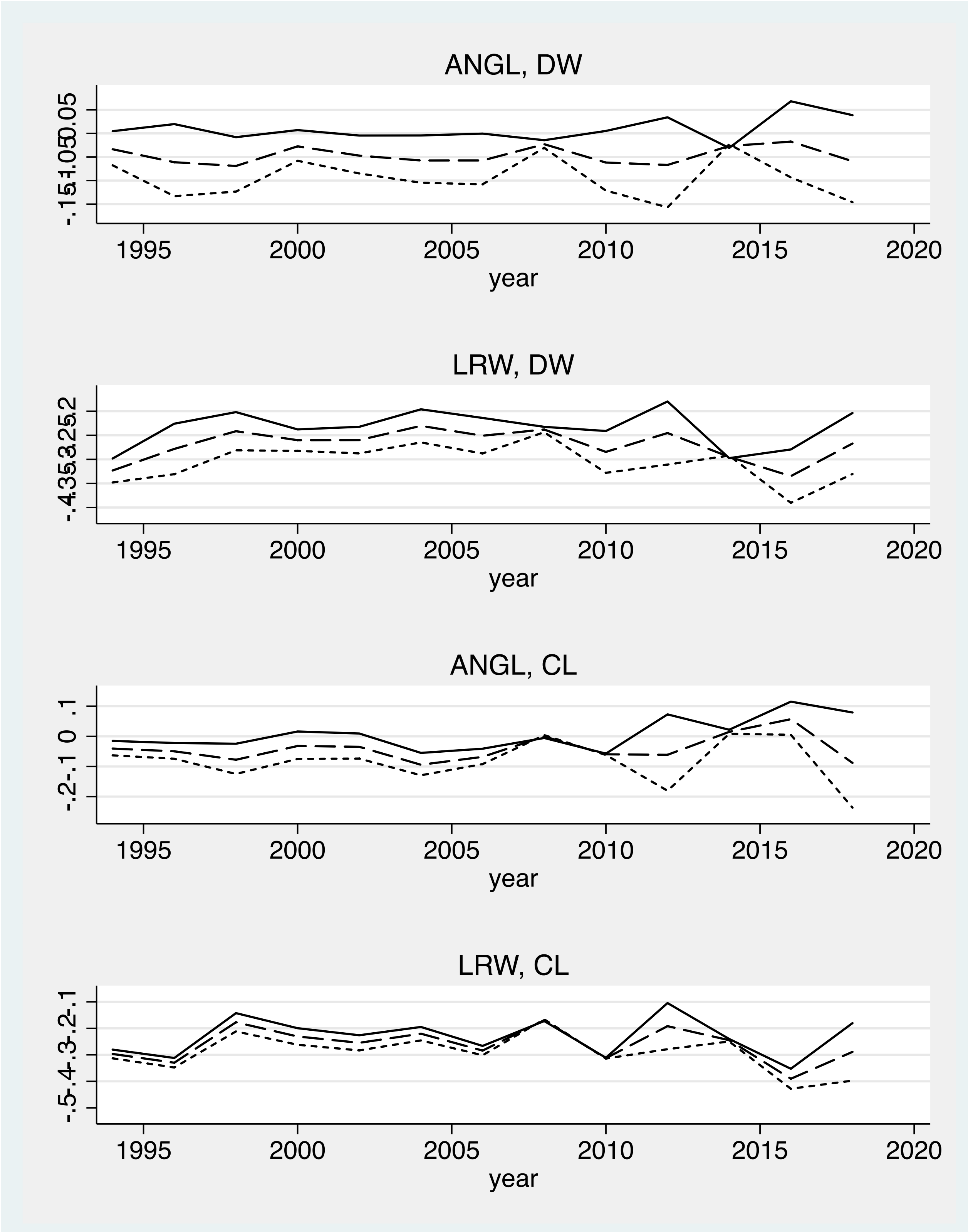

Figure H2: Wage Regressions Predicted Effects by Year: OLS Estimates

ANGL effects evaluated at log wages 5.8, 6.7, and 7.5; Effects of lost job wage evaluated at low, medium, and high *ANGL*.

Notes

[1] We also ignore the issue of unobservable ability *within* occupations (Blien et al., 2019).

[2] Only in the ΔSKL models estimated on the Continuously Employed Sample are the estimated coefficients on the interaction terms negative and statistically significant, but even here, the IV Kleibergen-Paap F statistic falls from 42.34 to 10.41, and the standard error is twice as large.

I Rank-Interaction Wage Models

The parsimonious rank-interaction specification is

$$\begin{aligned} \Delta W_{icl} = \beta_0 + \beta_W W_{il} + \beta_P LPCT_{ic} + \beta_S SKL_{ic} + \\ \beta_A ANGL_{icl} + \beta_{PA} ANGL_{icl} \times LPCT_{ic} + \beta_{SA} ANGL_{icl} \times LSKL + \beta_X X_i + \epsilon_{icl}, \end{aligned} \tag{I.1}$$

where ΔW_{icl} is the change in the log real wage between the lost and current job, and W_{il} is the real log wage on the lost job. OLS and IV estimates of the main coefficients of interest appear in Table I9, in Part A using the adjusted measures and in Part B using the unadjusted measures. There is no evidence of endogeneity bias, and so we focus on the OLS estimates.

The predicted effects are shown in the graphs at the top of Figure I3. In contrast to the ΔPCT analysis, the OLS estimated coefficients on $ANGL$ are negative, thus precluding evidence of career trajectory upgrading at low $LPCT$. However, as in the ΔSKL analysis, skill-broadening is still evident as a function of $LSKL$.[1] There is evidence of task specificity for both Juniors and Seniors throughout the $LPCT$ and $LSKL$ distributions. Although the predicted effects of $LPCT$ and $LSKL$ decrease in $ANGL$, the predicted effects are positive at low and medium $ANGL$, and are not significantly different than zero at high $ANGL$. We attribute the difference to the fact that $LPCT$ and $LSKL$ measure only imperfectly the relevant rank measure here, namely, lost job wages.

The **Junior-Senior Rank-Interaction Wage Change** model is

$$\begin{aligned} \Delta W_{icl} = \beta_0 + \beta_W W_{il} + \\ I(JR) \times \{\beta_{PJ} LPCT_{ic} + \beta_{SJ} LSKL_{ic} + \beta_{AJ} A_{icl} + \beta_{PAJ} A_{icl} \times LPCT_{ic} + \beta_{SAJ} A_{icl} \times LSKL\} + \\ I(SR) \times \{\beta_{PS} LPCT_{ic} + \beta_{SS} LSKL_{ic} + \beta_{AS} A_{icl} + \beta_{PAS} A_{icl} \times LPCT_{ic} + \beta_{SAS} A_{icl} \times LSKL\} + \\ \beta_X X_i + \epsilon_{icl}, \end{aligned} \tag{I.2}$$

where $ANGL_{icl}$ is abbreviated to A_{icl}. Out of the multitude of possibilities, we restrict ourselves to defining Junior cutoffs on alternatively $LPCT$ and $LSKL$.[2] Diagnostics for Equation I.2 are shown in Table I10. Predicted effects in Figure I3 show just two possible cutoffs. Results for additional cutoffs, contained in Figures I4 and I5, reinforce the main findings: limited evidence of career trajectory upgrading at lower ranks, and evidence of task specificity at higher ranks.

For the Junior-Senior specification (Appendix Equation I.2), we consider definitions of Junior status based, alternatively, on $LPCT$ and $LSKL$ cutoffs. The diagnostics suggest that a focus on the OLS estimates is appropriate (Appendix Table I10). The null hypothesis of Junior-Senior coefficient equality is rejected in the Displaced Worker sample virtually across the board, but at only a limited number of cutoffs in the Plant Closure sample.

Predicted effects are shown for Junior cutoffs of $LPCT = 30$ in the middle row of Figure I3, and for a cutoff of $LSKL = 30$ in the last row. Task specificity as a function of both $LPCT$ and $LSKL$ is readily evident for Senior workers. The (negative) predicted effects of $ANGL$ for Juniors rise in $LPCT$; although not inconsistent with the model, this rising pattern is not robust to other choices of cutoff. Only limited evidence of career trajectory upgrading for Juniors as a function of $LSKL$ is visible. Results for additional cutoffs are presented in Appendix Figures I4 and I5.

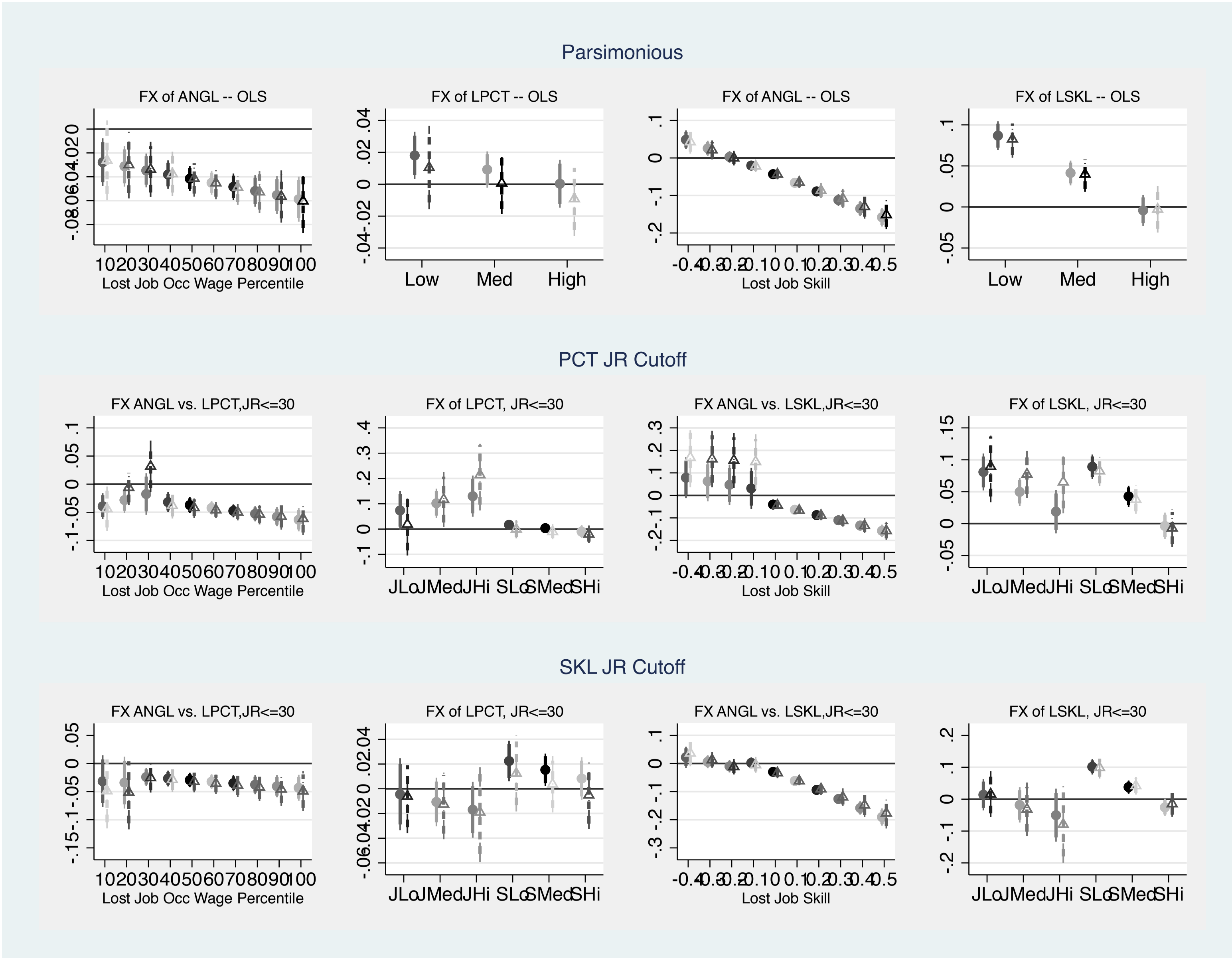

Figure I3: OLS Predicted Wage Effects, Rank-Interaction Model

Filled circles = Displaced Sample, open triangles=Plant Closure Sample. Because $ANGL$ interacts with both $LPCT$ and $LSKL$, the predicted effects as a function of $LPCT$ ($LSKL$) hold constant $LSKL$ ($LPCT$) at its mean value.

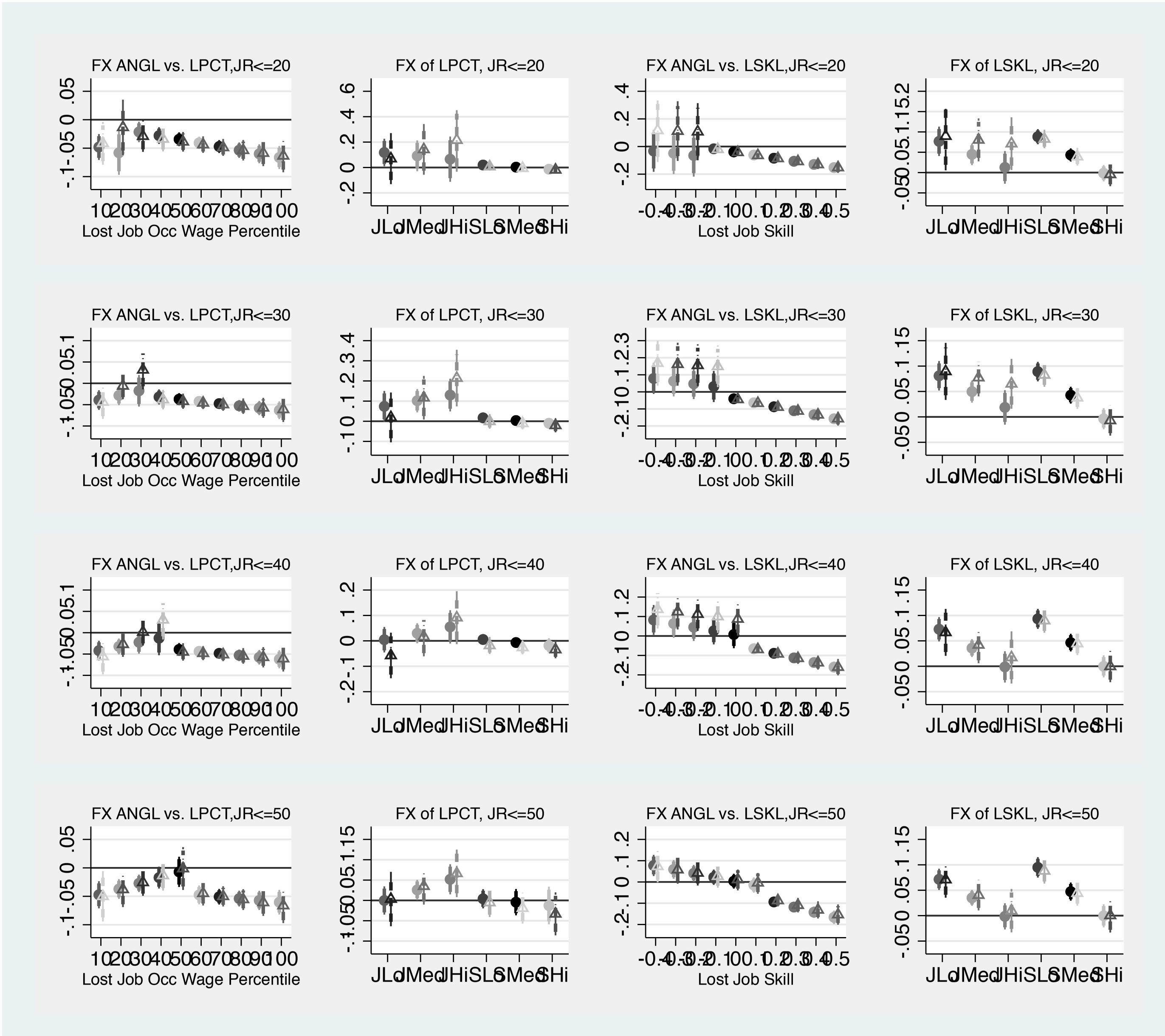

Figure I4: OLS Predicted Wage Effects, Junior-Senior Rank-Interaction Model: *PCT* Cutoffs

Filled circles = Displaced Sample, Open triangles=Plant Closure Sample. Predicted effects and 90/95% confidence intervals based on IV estimation of Equation I.2, with selected *LPCT*-based Junior cutoffs. Because *ANGL* interacts with both *LPCT* and *LSKL*, the predicted effects as a function of *LPCT* (*LSKL*) hold constant *LSKL* (*LPCT*) at its mean value.

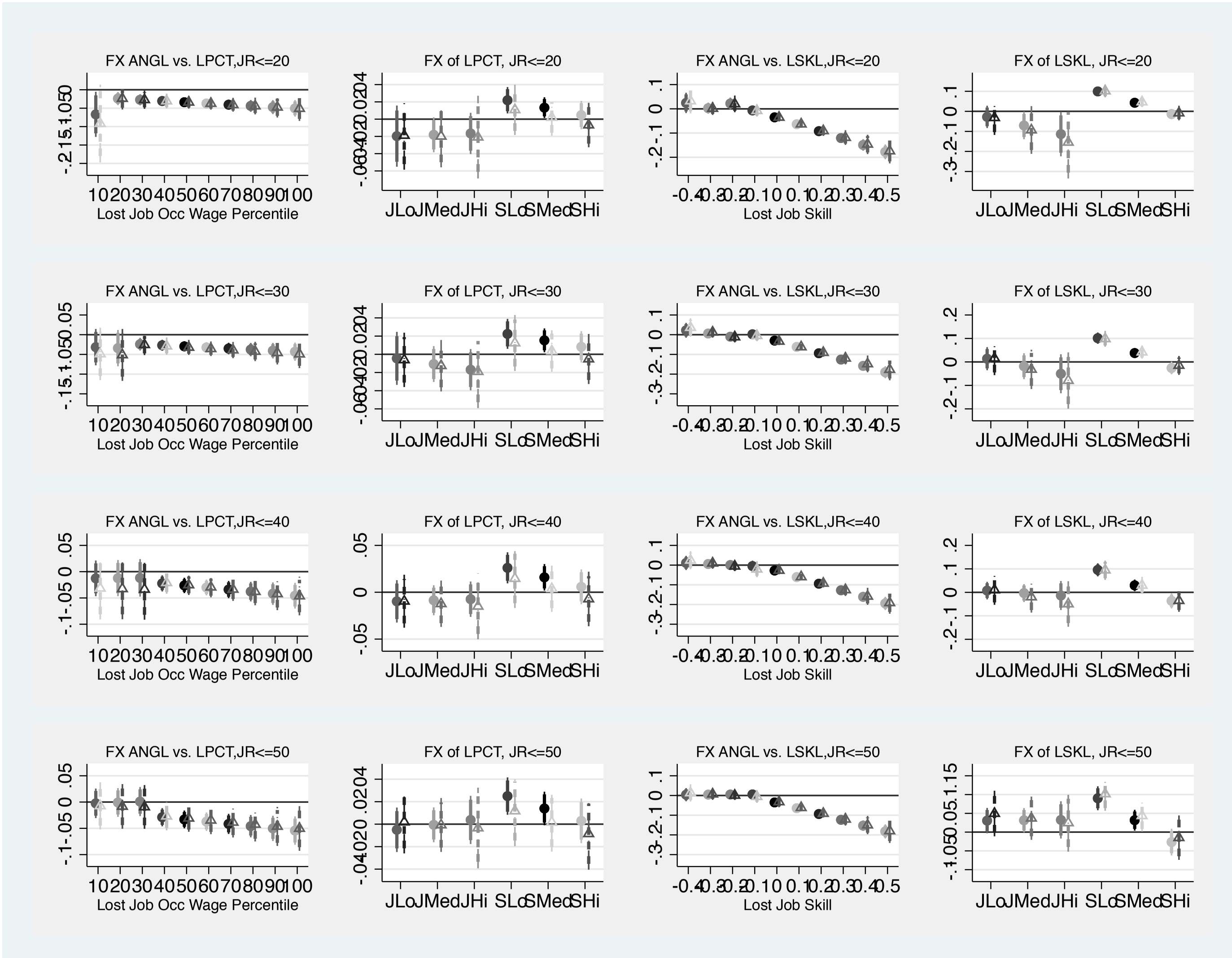

Figure I5: OLS Predicted Wage Effects, Junior-Senior Rank-Interaction Model: *SKL* Cutoffs

Filled circles = Displaced Sample, Open triangles=Plant Closure Sample. Predicted effects and 90/95% confidence intervals based on IV estimation of Equation I.2, with selected *LPCT*-based Junior cutoffs. Because *ANGL* interacts with both *LPCT* and *LSKL*, the predicted effects as a function of *LPCT* (*LSKL*) hold constant *LSKL* (*LPCT*) at its mean value.

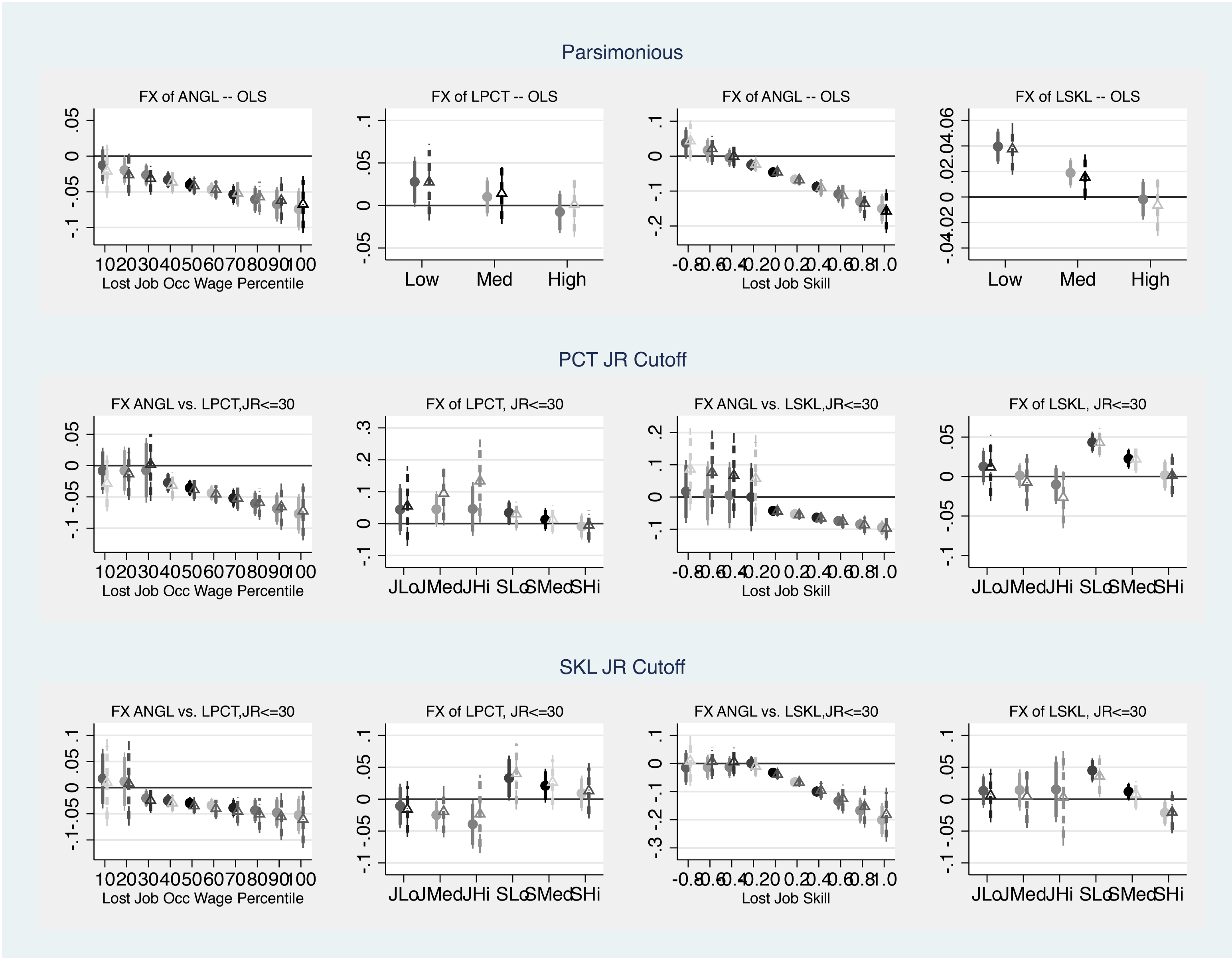

Figure I6: OLS Predicted Wage Effects, Rank-Interaction Model; Unadjusted Measures

Filled circles = Displaced Sample, open triangles=Plant Closure Sample. Because *ANGL* interacts with both *LPCT* and *LSKL*, the predicted effects as a function of *LPCT* (*LSKL*) hold constant *LSKL* (*LPCT*) at its mean value.

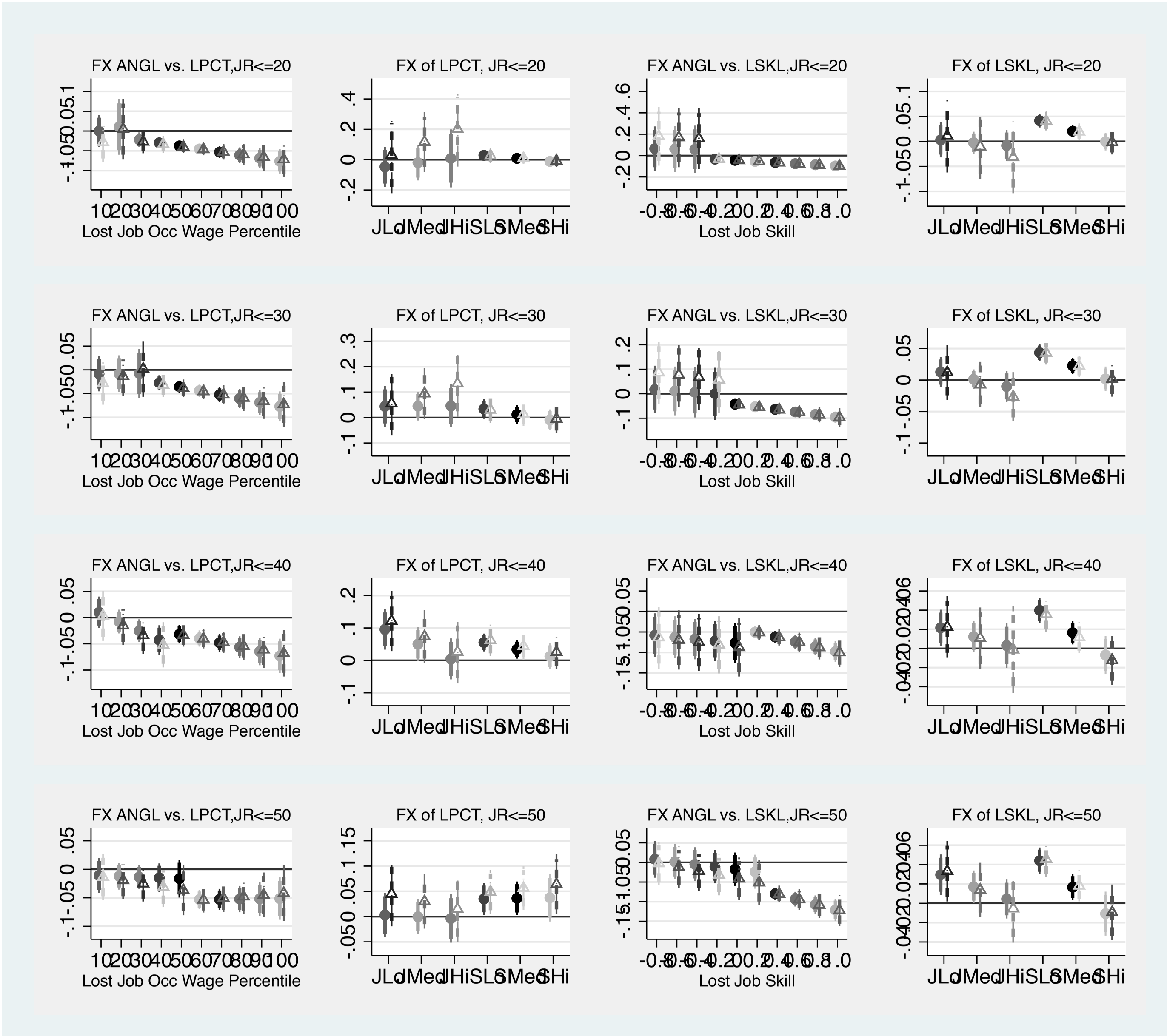

Figure I7: OLS Predicted Wage Effects, Junior-Senior Rank-Interaction Model: Unadjusted PCT Cutoffs

Filled circles = Displaced Sample, Open triangles=Plant Closure Sample. Predicted effects and 90/95% confidence intervals based on IV estimation of Equation I.2, with selected $LPCT$-based Junior cutoffs. Because $ANGL$ interacts with both $LPCT$ and $LSKL$, the predicted effects as a function of $LPCT$ ($LSKL$) hold constant $LSKL$ ($LPCT$) at its mean value.

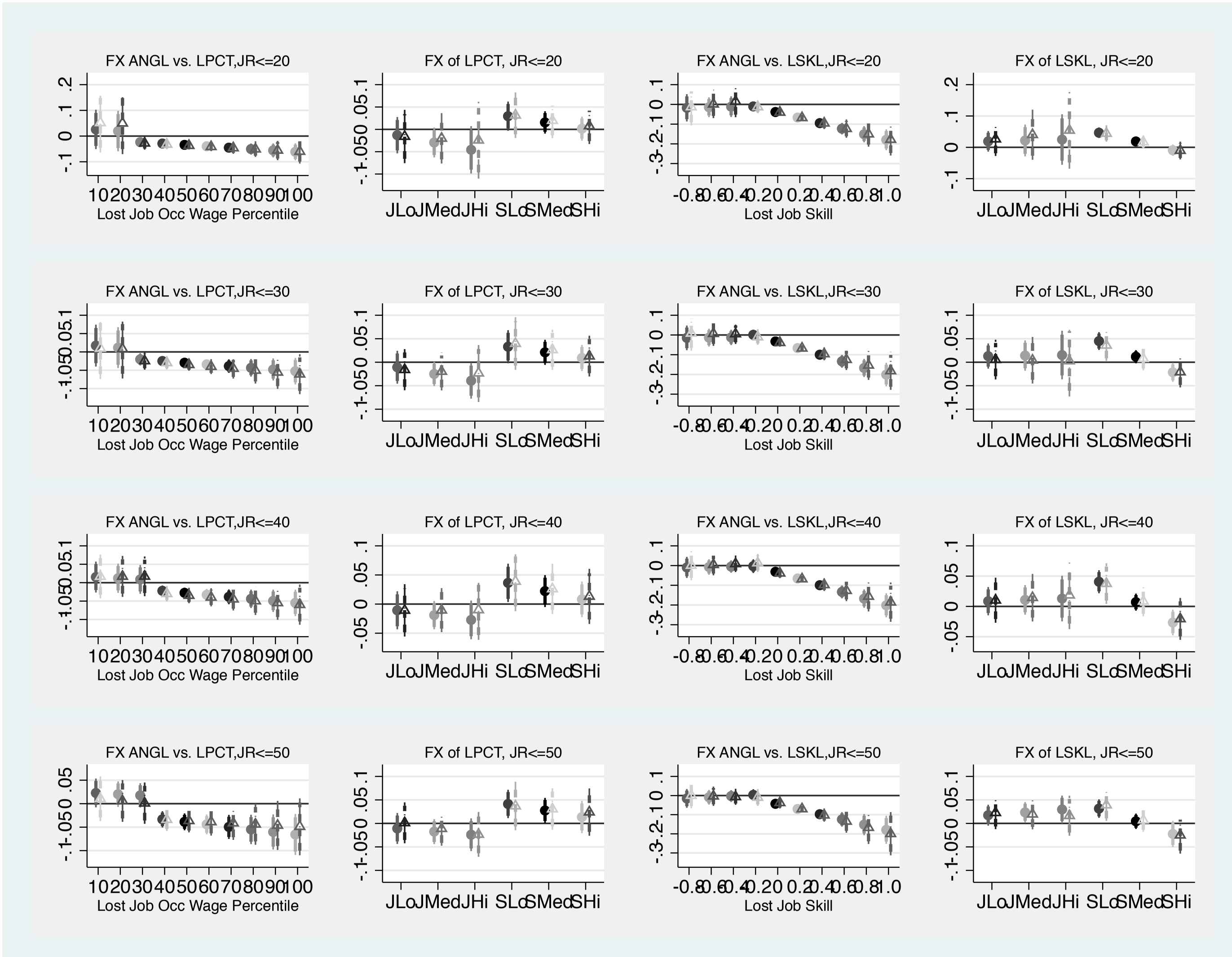

Figure I8: OLS Predicted Wage Effects, Junior-Senior Rank-Interaction Model: Unadjusted SKL Cutoffs

Filled circles = Displaced Sample, Open triangles=Plant Closure Sample. Predicted effects and 90/95% confidence intervals based on IV estimation of Equation I.2, with selected $LPCT$-based Junior cutoffs. Because $ANGL$ interacts with both $LPCT$ and $LSKL$, the predicted effects as a function of $LPCT$ ($LSKL$) hold constant $LSKL$ ($LPCT$) at its mean value.

Table I9: Wage Change Regressions: Rank Interaction Model

	A. Adjusted Rank Measures					
	Displaced		Plant Closed		Comparison	
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
LPCT	0.0010	0.0026	0.0008	0.0012	0.0015	0.0019
	(0.0004)	(0.0013)	(0.0007)	(0.0025)	(0.0002)	(0.0007)
LSKL	0.6526	0.7313	0.6185	0.8596	0.5816	0.4529
	(0.0604)	(0.2401)	(0.0783)	(0.4215)	(0.0270)	(0.1173)
ANGL	-0.0007	0.0018	-0.0006	0.0005	-0.0000	-0.0001
	(0.0003)	(0.0012)	(0.0006)	(0.0021)	(0.0002)	(0.0007)
$\times LPCT/100$	-0.0010	-0.0031	-0.0011	-0.0015	-0.0008	-0.0017
	(0.0006)	(0.0018)	(0.0009)	(0.0033)	(0.0003)	(0.0012)
$\times LSKL$	-0.0067	-0.0079	-0.0063	-0.0101	-0.0057	-0.0036
	(0.0007)	(0.0036)	(0.0011)	(0.0064)	(0.0003)	(0.0019)
Endog Chi-Sq		5.193		1.833		3.751
Endog P-Val		.1582		.6078		.2897
Kleibergen-Paap F		41		13		37
Observations	9589	9586	3521	3519	196829	196288
	B. Unadjusted Rank Measures					
	Displaced		Plant Closed		Comparison	
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
LPCT	0.0017	0.0030	0.0015	0.0052	0.0025	0.0028
	(0.0008)	(0.0027)	(0.0012)	(0.0047)	(0.0005)	(0.0016)
LSKL	0.2972	0.3090	0.2943	0.2986	0.2189	0.1372
	(0.0520)	(0.2415)	(0.0721)	(0.4335)	(0.0250)	(0.0985)
ANGL	-0.0002	0.0018	-0.0004	0.0035	0.0002	0.0002
	(0.0005)	(0.0022)	(0.0007)	(0.0039)	(0.0003)	(0.0016)
$\times LPCT/100$	-0.0020	-0.0036	-0.0015	-0.0063	-0.0012	-0.0019
	(0.0009)	(0.0036)	(0.0012)	(0.0062)	(0.0005)	(0.0023)
$\times LSKL$	-0.0031	-0.0034	-0.0033	-0.0039	-0.0029	-0.0015
	(0.0007)	(0.0036)	(0.0010)	(0.0064)	(0.0004)	(0.0017)
Tenure	Yes	Yes	Yes	Yes	No	No
Age	Yes	Yes	Yes	Yes	Yes	Yes
Education	Yes	Yes	Yes	Yes	Yes	Yes
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Displ Year Effects	Yes	Yes	Yes	Yes	No	No
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
Endog Chi-Sq		3.463		4.454		1.156
Endog P-Val		.3256		.2164		.7635
Kleibergen-Paap F		13		6.7		16
Observations	9589	9586	3521	3519	196829	196288

This Table contains selected coefficients for estimates of Equation I.1 on the Earnings Samples. Standard errors clustered on IPUMS 1990 occupation are in parentheses.

Table I10: Wage Change Analysis, Junior-Senior Rank-Interaction Specification: Diagnostic Tests

Dec. Cut	Displaced Sample: Endog (1)	EQ, IV (2)	RMSE (3)	EQ, LS (4)	RMSE (5)	Plant Closure Sample: Endog (6)	EQ, IV (7)	RMSE (8)	EQ, LS (9)	RMSE (10)
					Adjusted *PCT* Cutoffs					
1	0.191	0.303	0.391	0.155	0.389	0.608	0.999	0.474	0.000	0.377
2	0.384	0.388	0.390	0.012	0.389	0.791	0.514	0.382	0.036	0.377
3	0.113	0.117	0.391	0.017	0.389	0.588	0.219	0.377	0.005	0.376
4	0.083	0.082	0.393	0.180	0.389	0.402	0.010	0.383	0.017	0.376
5	0.136	0.069	0.391	0.023	0.389	0.294	0.015	0.379	0.043	0.377
6	0.094	0.082	0.392	0.071	0.389	0.033	0.014	0.387	0.131	0.377
7	0.026	0.162	0.391	0.044	0.389	0.101	0.141	0.382	0.232	0.377
8	0.040	0.002	0.391	0.000	0.389	0.472	0.230	0.377	0.228	0.377
9	0.025	0.039	0.398	0.946	0.389	0.280	0.999	1.339	0.742	0.377
					Adjusted *SKL* Cutoffs					
1	0.218	0.004	0.393	0.001	0.389	0.177	1.000	2.699	0.129	0.377
2	0.274	0.166	0.399	0.000	0.389	0.623	0.878	0.539	0.053	0.377
3	0.356	0.178	0.392	0.000	0.389	0.667	1.000	2.782	0.294	0.377
4	0.346	0.115	0.397	0.000	0.389	0.614	0.937	0.952	0.025	0.376
5	0.424	0.801	0.395	0.003	0.389	0.374	0.461	0.395	0.618	0.377
6	0.527	0.471	0.392	0.005	0.389	0.230	0.135	0.380	0.242	0.377
7	0.140	0.673	0.394	0.147	0.389	0.072	0.426	0.391	0.485	0.377
8	0.033	0.269	0.414	0.077	0.389	0.155	0.886	0.483	0.276	0.377
9	0.117	1.000	1.111	0.608	0.389	0.560	0.479	0.382	0.303	0.377
					Unadjusted *PCT* Cutoffs					
1	0.423	0.274	0.392	0.366	0.389	0.123	0.902	0.406	0.751	0.377
2	0.554	0.150	0.391	0.379	0.389	0.305	0.101	0.420	0.673	0.377
3	0.320	0.008	0.392	0.043	0.389	0.225	0.004	0.388	0.153	0.376
4	0.343	0.065	0.391	0.009	0.389	0.363	0.349	0.381	0.084	0.376
5	0.191	0.008	0.392	0.068	0.389	0.096	0.004	0.387	0.039	0.376
6	0.039	0.001	0.394	0.000	0.389	0.171	0.016	0.382	0.007	0.376
7	0.034	0.009	0.395	0.019	0.389	0.252	0.041	0.385	0.014	0.376
8	0.139	0.027	0.402	0.026	0.389	0.322	0.273	0.407	0.009	0.376
9	0.259	0.012	0.402	0.000	0.389	0.152	0.714	0.607	0.092	0.376
					Unadjusted *SKL* Cutoffs					
1	0.550	0.992	0.557	0.023	0.389	0.120	0.438	0.471	0.526	0.377
2	0.599	0.711	0.409	0.028	0.389	0.089	0.993	0.918	0.391	0.377
3	0.711	0.117	0.396	0.001	0.389	0.314	0.486	0.430	0.179	0.377
4	0.540	0.023	0.393	0.000	0.389	0.335	0.421	0.398	0.142	0.377
5	0.803	0.211	0.390	0.000	0.389	0.372	0.149	0.386	0.252	0.377
6	0.359	0.033	0.391	0.008	0.389	0.192	0.225	0.388	0.072	0.376
7	0.191	0.179	0.391	0.049	0.389	0.092	0.659	0.408	0.790	0.377
8	0.051	0.336	0.423	0.120	0.389	0.248	0.903	0.508	0.575	0.377
9	0.225	0.434	0.396	0.573	0.390	0.421	0.480	0.383	0.318	0.377

Diagnostics for JR-SR rank interaction wage models. Endogeneity pvals: cols. 1, 6; JR-SR equality pvals (see Equation 9): 2, 4, 7, 9; root means square errors: cols. 3, 5, 8, 10.

Notes

[1]Because $ANGL$ interacts with both $LPCT$ and $LSKL$, the predicted effects graphed as a function of one hold constant the other at its median value.

[2]We also estimated a specification with only one interaction in $ANGL$ to enhance precision. "Letting the data speak," as we do, is not ideal – there are *six* endogenous variables in IV estimates of Equation I.2 – but avoids other difficulties. These considerations reinforce our decision to focus on the wage-interaction specification in the body of the paper.