Does Multiskilling Matter?

Evidence from Displaced Workers

Peter Kuhn,
University of California, Santa Barbara

Arthur Sweetman,
Queen's University

February 1, 2005

Using Displaced Worker Surveys merged with occupational information on multiskilling from other sources, we examine the relationship between multiskilling, earnings, and displacement-induced earnings losses. Overall, we find that workers in multiskilled jobs earn more, both in the multiskilled job and in the job they locate after displacement. Since the latter differential outweighs the former by a small but statistically significant amount, multiskilling mitigates displacement-induced earnings losses. Controlling for the total training time required for the job, however, multiskilling is associated with *lower* earnings in both the predisplacement- and postdisplacement jobs. Since the latter effect is smaller than the former, a small prophylactic effect against displacement-induced wage losses exists in this sense as well.

The authors can be contacted at: pjkuhn@econ.ucsb.edu, and sweetman@qsilver.queensu.ca.
We thank Dong Hun Cho for timely and accurate research assistance, and the W. E. Upjohn Instititute for Employment Research for financial support under its mini-grant program. Thomas DeLeire, Catherine Weinberger, and participants at the Chicago Federal Reserve Conference on *Job Loss: Causes, Consequences, and Policy Responses* provided helpful comments.

Does Multiskilling Matter?

Evidence from Displaced Workers

Using Displaced Worker Surveys merged with occupational information on multiskilling from other sources, we examine the relationship between multiskilling, earnings, and displacement-induced earnings losses. Overall, we find that workers in multiskilled jobs earn more, both in the multiskilled job and in the job they locate after displacement. Since the latter differential outweighs the former by a small but statistically significant amount, multiskilling mitigates displacement-induced earnings losses. Controlling for the total training time required for the job, however, multiskilling is associated with *lower* earnings in both the predisplacement- and postdisplacement jobs. Since the latter effect is smaller than the former, a small prophylactic effect against displacement-induced wage losses exists in this sense as well.

1. Introduction

It is now well known that displaced workers in the U.S. and in several other countries experience wage losses that increase with the worker's tenure on the lost job (see for example Kuhn, 2002). Authors have also asked how the magnitude of these wage losses varies with certain worker characteristics, such as age and gender (e.g. Crossley, Jones and Kuhn 1994; Farber 1997). With the exception of union status (Kuhn and Sweetman 1998, 1999) and industry (Gibbons and Katz 1992), however, economists have not, to our knowledge, related the earnings losses of displaced workers to the characteristics of the *jobs* they held before displacement.

The relation between the characteristics of jobs and the wage losses of workers displaced from them may be of interest for a variety of reasons. For example, wage loss patterns may be informative about whether rents earned by workers are related to a certain job characteristic, such as public sector or union status. Wage loss patterns may also be informative about workers' choices concerning skill acquisition and maintenance in a world where skill demand is uncertain: for example Kuhn and Sweetman (1999) have speculated that displaced union workers' high wage losses may be related to the low *ex ante* permanent layoff risk associated with those jobs, a factor which reduces the incentives for alternative skill maintenance.

In this paper, we examine the effects of one particular job characteristic – multiskilling—on the wage losses experienced by displaced workers. Recently, the management literature has promoted multiskilling of employees as beneficial to firms because it allows firms to adjust more quickly and easily to demand changes (e.g. Denton

1992; Gomar et. Al. 2002). Further, Carmichael and MacLeod (1993) have argued that --because it assures workers of greater job security-- multiskilling should increase workers' willingness to share productivity-enhancing information with firms. A final potential benefit of multiskilling that is mentioned less often in the management literature (for obvious reasons) is that it may improve *workers'* chances of finding a good new job in the event of a separation. This prediction also follows naturally from the definition of *alternative* skills, introduced in Kuhn and Sweetman (1999), and the closely-related skill-weights approach to firm-specific capital (Lazear 2003).

Do workers displaced from jobs where they use a wide variety of skills experience smaller wage losses than other workers when those jobs disappear? If so, is this extra degree of security "purchased" at the cost of lower wages in the predisplacement job? Depending on the answers to these questions, any trend towards multiskilling may have had an unanticipated benefit, by making workers less vulnerable to job loss at a relatively low cost in terms of current earnings. These are the questions addressed in the current paper.

2. Data

The indicators of multiskilling used in this paper are taken from two sources –the 1977 Quality of Employment Survey (QES) and the 1980 Dictionary of Occupational Titles (DOT). These are matched at the occupation (and in the QES case, industry) level to data on displaced workers' earnings taken from the 1984, 1986, 1988 and 1990 waves of the BLS's Displaced Worker Surveys (DWS). Since each DWS Survey contains information on displacements that occurred in the five calendar years preceding the survey, our analysis relates the earnings losses of workers displaced between 1979 and 1989 to the multiskilling rates of their occupations, as measured in the late 1970's.[1]

In more detail, unlike most household microdata sets, the second wave of the Quality of Employment Survey (QES), conducted in 1977 (Quinn and Staines, 1979), asked a series of detailed questions about the nature of respondents' jobs. Two seem to capture the notion of multiskilling quite well: "My job requires that I keep learning new things," and, "I get to do a number of different things on my job." For both questions, interviewees were asked to respond on a five point scale ranging from "strongly disagree" (1) to "strongly agree" (5). The survey also captures the respondent's industry and occupation, which were coded using the 1970 census classification. Because of the QES's relatively small sample size, we are able to calculate means of these responses only for very highly aggregated occupations and industries; these means are displayed in Appendix Tables 1 and 2. When matched to broad occupation and industry groups in the DWS, these give us a first, highly aggregated look at the form of the multiskilling-wage loss relationship.

Our second set of multiskilling measures is taken from the detailed characteristics of occupations incorporated in the 1980 Dictionary of Occupational Titles, matched to 3-digit occupational categories by England and Kilbourne (2002). In particular, we use four job characteristics, as assessed by the DOT's job evaluators: ROUTPREF, CREATPREF, REPCON and VARCH. At the detailed job level, ROUTPREF is an indicator variable indicating whether the job requires a preference for "activities of a routine, concrete, organized nature". In this paper, ROUTPREF measures the

[1] We decided that earnings loss information after 1990 would be too poorly matched with occupational characteristics from the late 1970's to warrant inclusion in our sample.

(employment-weighted) fraction of jobs in the 3-digit occupation with this characteristic[2]. Similarly, CREATPREF gives the fraction of jobs requiring a preference for "activities of an abstract and creative nature".[3] REPCON is the share of jobs requiring "adaptability to performing repetitive work, or to continuously performing the same work, according to set procedures, sequence or pace"; and VARCH gives the share of jobs requiring "adaptability to performing a variety of duties, often changing from one task to another of a different nature without loss of efficiency or composure".

In this paper, we match England and Kilbourne's three-digit means to the 1984-1990 DWS. We then compute a fifth, "summary" multiskilling measure (MSKILLS) as the first principal component of the above four measures (see Appendix Table A3 for the matrix of correlation coefficients among these four measures). Finally, for comparison with our QES results, and to assess the likely impact of classification error on our results, we also conduct some analysis of the DOT measures aggregated to a 2- and 1-digit occupational level. Means of our composite DOT multiskilling measure, MSKILLS, for these one-digit categories are presented in Appendix Table A4.

Note that the coefficients of interest in our analysis are macro-level variables included in individual level wage equations. As is well known the grouped nature of this type of regressor can lead to OLS standard errors being biased downwards even in the presence of small intra-class correlations (Kloek, 1981; Moulton, 1986). To address this

---

[2] See England and Kilbourne (2002) for a description of the aggregration procedure.

[3] By construction, the DOT's methodology forces ROUTPREF and CREATPREF to be negatively correlated. We present both results however since there is additional information in either one, conditional on the other.

issue we correct OLS standard errors for clustering and heteroskedasticity throughout the paper.[4]

3. The Benefits of Multiskilling: One-digit Multiskilling Indicators and Displaced Workers' Wage Losses

Brief descriptive statistics for our sample of job displacements are provided in Table 1. Since our interest is in wage change after displacement, only those displaced workers who were re-employed by the CPS interview date are included in this sample. The average displaced worker in our sample was 34 years old and experienced a wage loss of about 16 percent. 38 percent of displaced workers were women; 74 percent had held their predisplacement job for less than 6 years and only 43 percent had any education beyond high school. The workers are roughly evenly spread across elapsed years since the displacement occurred, though a lower share in the 4-5 year category may suggest some recall bias.[5]

Tables 2 and 3 begin our analysis by providing a preliminary look at how the "traditional" (log) wage change regressions familiar to economists studying displaced workers are affected by the introduction of a multiskilling measure. Both Tables use multiskilling measures derived from the QES, matched to workers in the DWS by one-digit occupation (Table 2) or one-digit industry (Table 3). Column 1 in both tables presents log wage change regressions without the multiskilling measure. The patterns are very familiar: Wage losses are rising in both age and predisplacement job tenure, and

[4] Of course, if the group size is not too large relative to the number of members of each group, GLS using a random effects approach could improve the efficiency of our estimates, relative to OLS. Further, in preliminary work on these data, Breusch and Pagan (1980) Lagrange multiplier tests suggested that the

decreasing in education.[6] Women experience slightly greater losses. When each multiskilling variable is introduced into the regressions reported in columns (2) and (3), the other coefficients do not change appreciably, but the multiskilling coefficients are highly statistically significant.[7] Since the first occupation-level measure's range is just over 1 (as seen in appendix table 1), the coefficient implies that being displaced from one of the least, compared to one of the most, multiskilled occupations is associated with about a 6.5% to 8.5% larger wage loss.

Figures 1 and 2 plot the predicted log wage changes from the regression in column 1 of Table 2 against the mean multiskilling measures used as regressors in columns 2 and 3. A clear upward slope is observed in both: Professional and technical occupations experience the smallest wage losses upon displacement and the highest levels of multiskilling, with laborers and operatives at the other end of the scale. The difference in wage losses between these two groups is economically large (under 10 log points versus over 20), and suggests a solution to long-standing puzzle in the displacement literature: why do the least-skilled (e.g. laborers) lose the most (in log terms) when displaced? *A priori*, one might expect general and specific skills to be complements, leading to smaller losses among the less skilled. Further, low-skill labor markets (such as fast food jobs) are often described as highly competitive, with workers close to indifference among a large number of low-rent jobs. The narrowness of duties in

---

intra-class correlation addressed by GLS is indeed present. On the other hand, results from Hausman-type tests also suggested that the random effects approach inherent in GLS is inappropriate.

[5] Any such bias will be controlled for here using a full set of years-since-displacement fixed effects.

[6] Note that age is specified as a linear function; we initially attempted a quadratic, but it was rejected by the data.

[7] If the two multiskilling measures are introduced into the same regression neither is statistically significant, which is not surprising since the correlation between the occupation-level means is about 0.96 (while that for industries is 0.92). In contrast, in the individual-level QES data, the correlation is 0.40.

low-skilled workers' jobs, and its impact on their ability to find new jobs that use those skills, may be part of the answer.

An alternative way to match the QES multiskilling measures to the DWS is by industry, rather than occupation. Table 3 explores whether this makes a difference to our results. The regression reported in column (1) is identical to that in Table 2, but with industry instead of occupation fixed effects, and the coefficients are very similar. As in Table 2, when the industry level variables are introduced they are found to be statistically significant and economically important. Scatter plots similar to Figures 1 and 2 are presented in Figures 3 and 4. The positive association is not quite as strong visually as in the previous Figures, but is nonetheless evident. Now, business and professional services have the highest levels of multiskilling and the smallest log wage losses, with manufacturing and transportation/communication/utilities at the other end of the scale.

For comparability with our QES results, Table 4 aggregrates the 3-digit occupations in the DOT classification into one-digit categories similar to the QES categories. Only specifications that include the multiskilling measure are reported, and these measures were standardized to allow for comparability across columns.[8] Clearly, the indicators that we expect to be negatively correlated with multiskilling (ROUTPREF and REPCON) are associated with larger displacement-induced wage losses, while those that should be positively associated with multiskilling (CREATPREF and VARCH) are associated with smaller losses (though the latter coefficient is not statistically significant). Our composite measure of multiskilling, calculated as the first principal component of the above four indicators, also appears to mitigate displacement-induced wage losses; a one

[8] For Table 4, standardization was performed at the three-digit level, prior to aggregation into one-digit occupation categories.

standard-deviation increase in this measure is associated with a wage loss that is 6.6 percentage points smaller.[9] Finally, Figure 5 presents predicted log wage changes by one-digit occupation (from a fixed effects model identical to column 1 of Tables 2 and 3) against our MSKILLS measure. Once again, a positive association is clear, with professional/technical occupations experiencing the smallest wage losses, and laborers, operatives and transportation occupations the largest.

4. Costs of Multiskilling: Predisplacement Wages and Training Time

So far we have shown that workers in broad occupation or industry groups characterized by high levels of multiskilling experience significantly smaller wage losses when displaced. This result is robust to several measures of multiskilling taken from two different data sources. One question that immediately arises in interpreting this result is whether workers "pay" for the extra earnings security attached to multiskilled jobs in the form of lower wages. In other words, lower wages might be a compensating differential for a job attribute (multiskilling) that is costly for employers to provide but valuable to workers.

To address this question, Table 5 replicates the regressions in Tables 2 through 4 for the *level* of predisplacement and postdisplacement wages in addition to wage changes. To allow for comparability of coefficients across different skill measures, all the multiskilling measures in Table 5 are standardized at the one-digit level.[10] Only the coefficients on the multiskilling measures are reported. Looking at all the occupation-

---

[9] MSKILLS was calculated at the three-digit occupation level using the following formula: MSKILLS = -.546*ROUTPREF + .538*CREATPREF - .513*REPCON + .385*VARCH. For Table 5, the resulting scores were then aggregated (using employment weights) to the one-digit level.

based measures, a very consistent pattern emerges: First, (treating ROUTPREF and REPCON as measures of "single-skilling", as is suggested by our principal component analysis) every measure of multiskilling is associated with higher, not lower earnings in the predisplacement job. Second, all measures of multiskilling are also associated with higher earnings in the postdisplacement job. Together, these findings suggest that our multiskilling measures may capturing some unmeasured component of skills that are portable across jobs. Third, however, in all seven cases the absolute magnitude of the multiskilling coefficient is greater in column 2 than in column 1: in other words, multiskilling in the predisplacement job has a larger positive effect on wages in the postdisplacement job than in the predisplacement job itself. This pattern is *not* consistent with the notion that multiskilling is a simply a noisy indicator of unmeasured general skills; that scenario would imply a smaller coefficient in column 2 than column 1. Finally, note that the coefficients in column 3, which are simply the algebraic difference between the column 1 and column 2 coefficients, continue to show that multiskilling is associated with smaller displacement-induced earnings losses.

The patterns across one-digit industry groups in Table 5 differ from those for occupation: if anything, multiskilled industries pay less than other industries, but the difference is small and statistically insignificant. Despite this, workers displaced from multiskilled industries earn more than observationally-identical workers displaced from "single-skilled" industries. While the latter effect is also statistically insignificant, the difference between the two above effects is significant, as is indicated by column 3 of the Table.

---

[10] Thus, the regressions in column 3 of Table 5 are identical to the corresponding wage-change regressions in Tables 2-4 except for scale.

In sum, Table 5 does not provide any evidence that workers pay for the extra security of multiskilled jobs in the form of lower wages. If anything, workers in these jobs earn higher wages, or similar wages, to observationally-equivalent workers in other occupations and industries. Further, the fact that multiskilling has a larger positive effect on postdisplacement than on predisplacement earnings strongly suggests it is not acting simply as a proxy for some poorly-measured unidimensional notion of general skill.

So far, all our results are based on comparisons across a small number of one-digit industries and occupations. While our standard errors adjust for this, it is natural to ask whether our results are robust to finer levels of aggregation. This issue is explored in Part A of Table 6, which focuses on our DOT data (the only data set where more disaggregated multiskilling measures are available). For brevity, we only report results for the composite multiskilling indicator, MSKILLS. For comparability across levels of aggregation, the MSKILLS measures are all standardized at the same level of aggregation (i.e. the variable is divided by its standard deviation at the three-digit level). According to the Table, the coefficients on MSKILLS are quite stable whether MSKILLS is measured as a one-, two- or three-digit occupational mean. While some decline in the estimated palliative effect of multiskilling on displacement-induced wage losses occurs as we move to the three-digit level, this is not unexpected given the greater likely role of classification error at higher levels of disaggregation.

Could our multiskilling index be acting as a proxy not for a particular *type* of training –training in a variety of tasks—but for the total *amount* of training?[11] Fortunately, the DOT data provide us with a way to address this question: each DOT job is coded with a variable, SVP (specific vocational preparation) that measures the amount of time it takes a typical employee to become proficient at it. Controlling for SVP thus provides a way of assessing the effects of changing the *type* of training --from a broad array of skills to a single, concentrated skill—while holding total training time constant.

Predisplacement wage, postdisplacement wage, and wage-change regressions identical to those considered previously but with an SVP control are summarized in part B of Table 6. The patterns are fascinating. First, note that (regardless of the level of aggregation) jobs requiring high total levels of training time (SVP) pay more than other jobs. Persons displaced from those jobs also earn more than other displaced people in their postdisplacement jobs, but --in contrast to the multiskilling "premium" in Table 5-- is not fully portable across jobs: the SVP coefficients in column 2 are all smaller than those in column 1. Second, note that once total training time is held constant, multiskilled jobs pay *less* than other jobs, in contrast to the previous results. Thus, in this different sense, there may be a compensating differential for multiskilling after all. Third, regardless of the level of aggregation, the wage discount associated with multiskilling in the predisplacment job is smaller in the post- than in the predisplacement job. Thus, as column 3 indicates, multiskilling still mitigates displacement-induced wage losses, even when the total amount of training in the predisplacement job is held constant.

A final concern addressed in this section is the following: perhaps the factor that really helps worker adapt easily to displacement is *education*: education could be either a signal of, or a cause of a greater ability to learn new skills after one's old skills are rendered obsolete. Since the educational categories held constant in our regressions are

---

[11] Even if this is the case, note that it does not necessarily help account for our finding that multiskilling mitigates wage losses; in fact, if even the smallest fraction of such training is firm-specific, one would

quite broad, it could be that our multiskilling indicator simply proxies for within-category heterogeneity in education. To assess this concern, we replicated our analysis for the subset of workers reporting exactly a high school degree as their highest level of education. When we did this, the three-digit MSKILLS coefficient on wage losses (in column 3 of Table 6) changed from .0087 (.0043) to .0104(.0051) in the “basic” specification, and from .0183(.0094) to .0302(.0132) in the specification with an SVP control. Thus, if anything, our results were strengthened. We conclude that our multiskills indicators are not simply proxying for unmeasured heterogeneity in education; rather they seem to be capturing a distinct aspect of multiskilled jobs or of the sorts of people inhabiting those jobs.

5. Summary

To our knowledge this is the first paper to explore how a characteristic of predisplacement jobs (other than union status or industry) affects postdisplacement outcomes. The characteristic we focus on here is the degree of multiskilling in the job. To address this issue, we obtained measures of multiskilling at the occupation and industry level from the Quality of Employment Survey and the Dictionary of Occupational Titles, and matched these to outcome data for individual workers in the Displaced Worker Surveys. The results confirm our expectations – that workers displaced from industries and occupations with higher levels of multiskilling experience, on average, smaller wage losses. This effect was robust to several measures of multiskillling, to the degree of aggregation at which occupations are classified, to

---

expect more of it to raise, not reduce, displacement-induced wage losses.

controls for the *total* amount of training time associated with an occupation, and to very tight controls for educational attainment.

Certain patterns in our results also provide clues regarding the mechanism via which multiskilling might mitigate wage losses. In particular, the multiskilling indicators in this paper have the following peculiar feature: they reflect a job characteristic that raises the earnings of persons inhabiting those jobs more in *alternative* employment than in the job itself. As such, this characteristic is strongly suggestive of the notion of alternative skills (Kuhn and Sweetman 1999), or of a "skill-weights" interpretation of firm-specific human capital (Lazear 2003).

Finally, a natural question is whether we can distinguish a scenario in which working in a multiskilled job causes workers to be less vulnerable to displacement from one in which "adaptable" workers self-select into multiskilled occupations. On the basis of the results in the current paper, the answer to this question is clearly "no": workers in our data are not randomly assigned to predisplacement jobs; thus there is no immediately obvious way of distinguishing the effects of worker versus job characteristics. Our results do, however, suggest that greater attention to issues of multiskilling and worker "adaptability" will increase our knowledge about what kinds of factors mitigate the severe earnings losses often associated with job displacement.

References

Breusch, T, and A. Pagan. “The Lagrange multiplier test and its application to model specification in econometrics,” Review of Economic Studies 47 (1980): 239-253.

Carmichael, L. and W. B. MacLeod. “Multiskilling and the Japanese Firm” Economic Journal 103 (416) (January 1993): 142-160.

Crossley, T., S. R. G. Jones, and P. Kuhn. "Gender Differences in Displacement Costs: Evidence and Implications" Journal of Human Resources 19 (Spring 1994), pp. 461-480.

Denton, D. K., “Multi-Skilled Teams Replace Old Work Systems” HRMagazine 37(9) (Sept. 1992): 48-54.

England, Paula, and Barbara Kilbourne “Occupational Measures from the Dictionary of Occupational Titles for 1980 Census Detailed Occupations”, (ICPSR 8942), 2002.

Farber, Henry. “The Changing Face of Job Loss in the United States, 1981-1995”. Brookings Papers on Economic Activity, Microeconomics 1997: 55-128.

Gibbons, R. and L. Katz. “Does Unmeasured Ability Explain Inter-industry Wage Differentials?” Review of Economic Studies, July 1992; 59(3): 515-35

Gomar, J., C. Haas and D. Morton. “Assignment and Allocation Optimization of Partially Multiskilled Workforce” Journal of Construction Engineering and Management 128(2) (Mar/Apr. 2002), 103-110.

Kloek, T. “OLS estimation in a model where a microvariable is explained by aggregates and contemporaneous disturbances are equicorrelated.” Econometrica 49(1) (1981): 205-207.

Kuhn, P., ed. Losing Work, Moving On: International Perspectives on Worker Displacement Kalamazoo, Mich.: W. E. Upjohn Institute for Employment Research, 2002.

Kuhn, P. and A. Sweetman. "Wage Loss Following Displacement: The Role of Union Coverage" Industrial and Labor Relations Review 51 (April 1998), pp. 384-400

Kuhn, P. and A. Sweetman. “Vulnerable Seniors: Unions, Tenure, and Wages Following Permanent Job Loss”. Journal of Labor Economics 17(4) (October 1999): 671-693.

Lazear, E. P. “Firm-Specific Human Capital: A Skill-Weights Approach”. NBER working paper no. 9679, May 2003.

Moulton, Brent R. “Random Group Effects and the Precision of Regression Estimates.” Journal of Econometrics 32 (1986): 385-397.

Quinn Robert, and Graham Staines, Principal Investigators, “Quality of Employment Survey, 1977: Cross-Section” (ICPSR 7689), 1979.

Table 1: Descriptive Statistics, DWS Sample

Variable	Mean
Change in log Wages	-0.16
Age at Displacement	34.4
Female	0.38
Predisplacement Job Tenure	
Up to one year	0.33
2-5 years	0.41
6-12 years	0.18
12-25 years	0.08
Education	
HS Incomplete	0.14
High School Graduate	0.43
Some College	0.23
College Degree	0.13
More than College	0.07
Years Since Displacement	
Less than one	0.20
1-2	0.22
2-3	0.22
3-4	0.20
4-5	0.16

Table 2: Determinants of Log Wage Changes in DWS Data, as a Function of Occupational Characteristics from 1977 Quality of Employment Survey

	(1)	(2)	(3)
Tenure on lost job:			
2-5 years	-.056** (.019)	-.056** (.020)	-.056** (.020)
6-12 years	-.135** (.016)	-.137** (.017)	-.137** (.017)
13-25 years	-.198** (.028)	-.210** (.029)	-.200** (.028)
Age at displacement (years)	-.005** (.001)	-.005** (.001)	-.005** (.001)
Female	-.030** (.018)	-.006 (.020)	-.008 (.019)
Learn New Things on Job? (scale from 1 (no) to 5 (yes))		.058** (.024)	
Do Different Things on Job? (scale from 1 (no) to 5 (yes))			.077** (.031)
High School Graduate	.035 (.022)	.037* (.019)	.037* (.019)
Some College	.026 (.016)	.033 (.018)	.032 (.017)
College Graduate	.066** (.022).	.076** (.020)	.077** (.018)
More than College Graduate	.107** (.033)	.115** (.031)	.118** (.030)
Occupation Fixed Effects?	Yes	No	No
Year-of-Displacement Fixed Effects?	Yes	Yes	Yes
Years-since-Displacement Fixed Effects?	Yes	Yes	Yes
R squared	.033	.029	.029
Number of observations	11758	11758	11758

**significant at 99 percent; * significant at 95 percent. Heteroskedasticity consistent standard errors in parentheses; errors are adjusted for clustering by occupation.

Nine occupational categories were used: See Appendix Table A1 for details. Occupations in primary industries were excluded due to small sample sizes. Transportation occupations were excluded because they could not be matched in a straightforward way to the QES classification.

Table 3: Determinants of Log Wage Changes in DWS Data, as a Function of Industry Characteristics from 1977 Quality of Employment Survey

	(1)	(2)	(3)
Tenure on lost job:			
2-5 years	-.052** (.013)	-.052** (.015)	-.051** (.014)
6-12 years	-.133** (.025)	-.132** (.027)	-.131** (.026)
13-25 years	-.192** (.018)	-.192** (.023)	-.188** (.021)
Age at displacement (years)	-.005** (.001)	-.005** (.001)	-.005** (.001)
Female	-.032** (.015)	-.018 (.022)	-.017 (.024)
Learn New Things on Job? (scale from 1 (no) to 5 (yes))		.107** (.016)	
Do Different Things on Job? (scale from 1 (no) to 5 (yes))			.151** (.051)
High School Graduate	.040 (.011)	.042** (.019)	.041** (.012)
Some College	.038* (.015)	.039** (.013)	.032 (.017)
College Graduate	.086** (.011).	.089** (.010)	.091** (.010)
Graduate Degree	.135** (.034)	134** (.032)	.137** (.030)
Occupation Fixed Effects?	Yes	No	No
Year-of-Displacement Fixed Effects?	Yes	Yes	Yes
Years-since-Displacement Fixed Effects?	Yes	Yes	Yes
R squared	.034	.032	.033
Number of observations	11969	11969	11969

**significant at 99 percent; * significant at 95 percent.Heteroskedasticity consistent standard errors in parentheses; errors are adjusted for clustering by industry.

Ten industry categories were used: see Appendix Table A2 for details. Primary industries were dropped due to small sample sizes.

Table 4: Determinants of Log Wage Changes in DWS Data, as a Function of Occupational Characteristics from 1980 Dictionary of Occupational Titles: One-Digit Groups

	Multiskilling Indicator				
	ROUTPREF	CREATPREF	REPCON	VARCH	MS
Tenure on lost job:					
2-5 years	-.053** (.019)	-.055** (.019)	-.054** (.019)	-.052** (.019)	-.053** (.019)
6-12 years	-.140** (.016)	-.140** (.016)	-.139** (.016)	-.139** (.016)	-.140** (.016)
13-25 years	-.199** (.027)	-.199** (.027)	-.197** (.026)	-.197** (.026)	-.198** (.027)
Age at displacement (years)	-.005** (.001)	-.005** (.001)	-.005** (.001)	-.005** (.001)	-.005** (.001)
Female	-.001 (.021)	-.002 (.021)	-.007 (.019)	-.002 (.019)	-.002 (.021)
Multiskilling Indicator	-.022 (.015)	.025 (.014)	-.042** (.010)	.031 (.022)	.017* (.008)
High School Graduate	.038* (.018)	.037* (.018)	.032 (.018)	.039** (.016)	.035 (.018)
Some College	.037 (.019)	.036 (.0219	.025 (.018)	.039** (.016)	.033 (.018)
College Graduate	.086** (.017)	.083** (.017)	.068** (.020)	.092** (.015)	.079** (.019)
More than College	.137** (.031)	.131** (.029)	.118** (.029)	.145** (.028)	.128** (.028)
Adjusted R squared	.029	.030	.031	.030	.030
Number of observations	12500	12500	12500	12500	12507

**significant at 99 percent; * significant at 95 percent. Heteroskedasticity consistent standard errors in parentheses; adjusted for clustering by occupation. All regressions include a full set of fixed effects for year of displacement and for elapsed years since displacement.

Ten occupation categories were used: see Table A4 for details. Occupations in primary industries were dropped due to small sample sizes.

Table 5: Determinants of Log Wages in DWS Data, as a Function of Occupational Characteristics from 1980 Dictionary of Occupational Titles: One-Digit Groups

	Dependent Variable		
	(1)	(2)	(3)
Multiskilling Measure:	Predisplacement log wage	Postdisplacement log wage	Change in log wage
QES Occupation Means:			
"Learn New Things"	.0898** (.0350)	.1144** (.0268)	.0246** (.0100)
"Do Different Things"	.0806* (.0353)	.1054** (.0284)	.0248** (.0100)
QES Industry Means:			
"Learn New Things"	-.0170 (.0151)	.0113 (.0114)	.0283** (.0044)
"Do Different Things"	-.0302 (.0258)	.0010 (.0158)	.0313** (.0109)
DOT Occupation Means:			
ROUTPREF	-.0861** (.0297)	-.1028** (.0238)	-.0166 (.0114)
CREATPREF	.0821** (.0281)	.1008** (.0237)	.0188 (.0105)
REPCON	-.0638* (.0282)	-.0950** (.0232)	-.0312** (.0076)
VARCH	.0588* (.0259)	.0761** (.0189)	.0173 (.0123)
"Mskills"	.0806** (.0271)	.1035** (.0209)	.0229* (.0103)

**significant at 99 percent; * significant at 95 percent. Heteroskedasticity consistent standard errors in parentheses; adjusted for clustering by occupation or industry. In addition to the controls shown in Tables 2-4 (tenure, age, gender and education), all regressions include a full set of fixed effects for year of displacement and for elapsed years since displacement.

All multiskilling indicators standardized at the one-digit level.

Table 6: Coefficients on Predisplacement Multiskilling Index (MSKILLS) and Length of Training Period (SVP), Various Specifications and Levels of Aggregation

	Dependent Variable		
Specification and Level of Aggregation	Predisplacement log wage	Postdisplacement log wage	Change in log wage
A. Basic Specification (no SVP control)			
One digit occupation:			
Mskills	.0607** (.0204)	.0779** .0157)	.0172* (.0078)
Two digit occupation:			
Mskills	.0668** (.0149)	.0734** (.0135)	.0066 (.0073)
Three digit occupation:			
Mskills	.0519** (.0106)	.0605** (.0095)	.0087* (.0043)
B. Specification including SVP control			
One digit occupation:			
Mskills	-.1592** (.0528)	-.0808 (.0470)	.0784** (.0128)
SVP	.3854** (.0996)	.2781** (.0818)	-.1073** (.0264)
Two digit occupation:			
Mskills	-.0821* (.0618)	-.0549* (.0281)	.0272 (.0156)
SVP	.2758** (.0618)	.2376** (.0439)	-.0382 (.0301)
Three digit occupation:			
Mskills	-.0383* (.0195)	-.0200 (.0164)	.0183* (.0094)
SVP	.1829** (.0312)	.1633** (.0251)	-.0196 (.0169)

**significant at 99 percent; * significant at 95 percent. Heteroskedasticity consistent standard errors in parentheses, adjusted for clustering by predisplacement occupation at the level of aggregation indicated. In addition to the controls shown in Tables 2-4 (tenure, age, gender and education), all regressions include controls for predisplacement job tenure, age, education, gender, plus a full set of fixed effects for year of displacement and for elapsed years since displacement.

Regardless of the level of aggregation, MSKILLS and SVP scores are standardized at the three-digit level.

Appendix

Table A1: Multiskilling Indicators by Occupation, 1977 Quality of Employment Survey

	Learn New Things?	Do Different Things?
Professional	4.63	4.32
Technical	4.49	4.27
Executive, Managerial	4.42	4.40
Sales	4.25	4.10
Clerical	4.01	4.07
Craft and Precision Production	4.22	4.11
Machine Operators, Assemblers	3.29	3.38
Laborers, Helpers	3.54	3.74
Service	3.78	3.94

Table A2: Multiskilling Indicators by Industry, 1977 Quality of Employment Survey

	Learn New Things?	Do Different Things?
Construction	4.08	4.19
Manufacturing	3.70	3.74
Transportation, Communication, Utilities	3.88	3.80
Wholesale Trade	4.11	4.11
Retail Trade	3.97	4.07
Finance, Insurance, Real Estate	4.21	4.09
Business Services	4.52	4.24
Personal Services	3.97	4.03
Professional Services	4.40	4.24
Public Administration	4.25	4.23

Table A3: Correlation Coefficients among DOT Multiskilling Measures

	ROUTPREF	CREATPREF	REPCON	VARCH
ROUTPREF	1.000			
CREATPREF	-.961	1.000		
REPCON	.782	-.753	1.000	
VARCH	-.480	.453	-.531	1.000

Table A4: Multiskilling Indicator Means by Occupation, Dictionary of Occupational Titles

Professional	1.44
Technical	1.79
Executive, Managerial	1.20
Sales	0.59
Clerical	-0.52
Craft and Precision Production	0.94
Machine Operators, Assemblers	-1.57
Laborers, Helpers	-2.19
Service	-0.42
Transportation	-2.24

Multiskilling indicator is the standardized first principal component of the four multiskilling measures in Table A4.

Figure 1: Predicted log Wage Change by Occupation versus QES "Learn New Things" Indicator

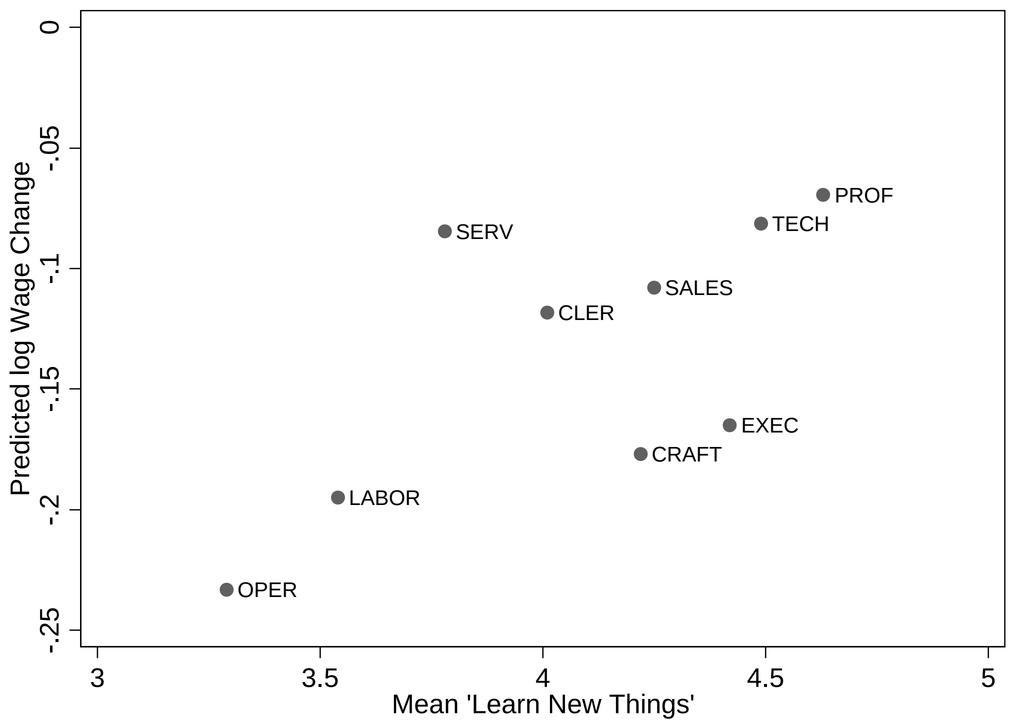

Figure 2: Predicted log Wage Change by Occupation versus QES "Do Different Things" Indicator

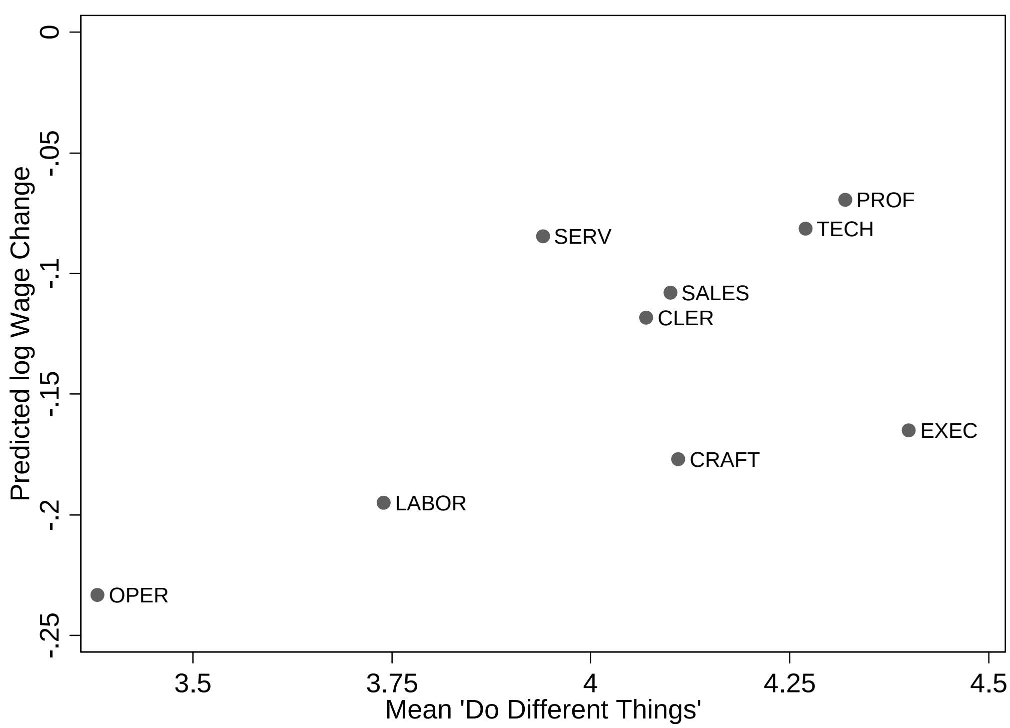

Figure 3: Predicted log Wage Change by Industry versus QES "Learn New Things" Indicator

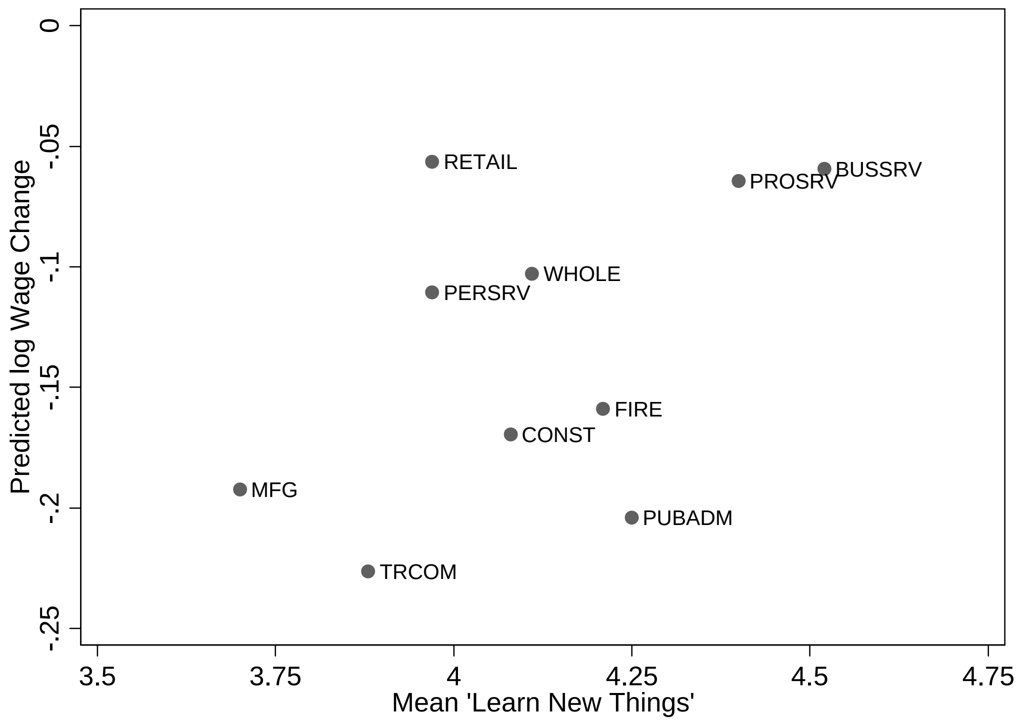

Figure 4: Predicted log Wage Change by Industry versus QES "Do Different Things" Indicator

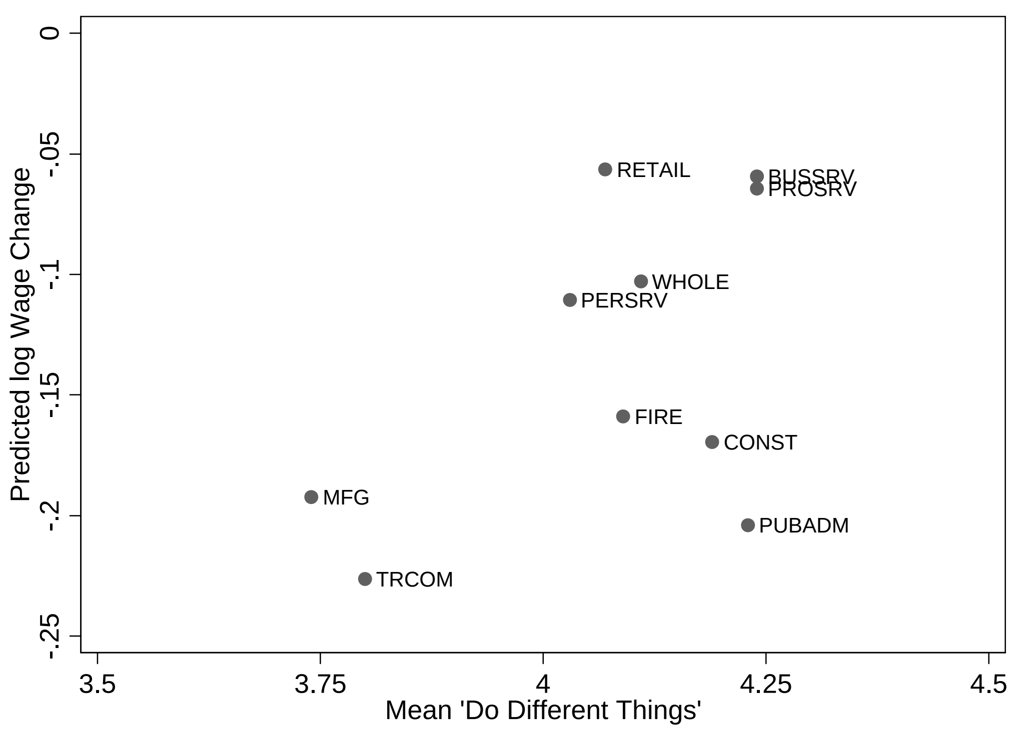

Figure 5: Predicted log Wage Change by Occupation versus DOT Multiskilling Index