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An Empirical Study on Industry-specific Components of Productivity*

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〈Contents〉

I. Introduction

Two well-known facts established in the labor economics literature are (i) a positive relationship between earnings and current job tenure, and (ii) a negative relationship between the probability of job separation and tenure (see for example Borjas and Mincer (1978) and Mincer and Jovanovic (1981)).

The theory of human capital (Becker (1962), Oi (1962), Hashimoto (1981)) provides a consistent explanation of these relationships. According to the human capital theory, workers accumulate firm-specific human capital while employed, and hence wages rise

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above the wage rate attainable in the market as tenure progresses. Firm-specific human capital makes worker-firm separation costly, regardless of which party incurs the cost of firm-specific training, and thus discourages both quits and layoffs, leading to a negative relationship between turnover and tenure.

The distinction between firm-specific and general human capital is based on the extent to which human capital can be transferred across jobs. Firm-specific training is defined as training that increases a person's productivity only in the firm in which he is trained, while general training increases a worker's productivity regardless of where he is employed. In empirical studies, firm-specific and general human capital are measured by job tenure and labor market experience, respectively, and both are found to be strongly positively correlated with wage rates or earnings, supporting the human capital theory.

Firm-specific and general human capital are, however, two extreme types of human capital in terms of across-job transferability, and hence may not be sufficient to adequately represent one's productivity. A few recent studies (Shaw (1984), McCall (1990)) introduce occupation-specific components of workers' productivity. These studies provide evidence for the importance of occupation affiliation and suggest a similar effect of industry affiliation.

This paper attempts to identify industry-specific components of human capital. This is done by investigating the effect of industry tenure on two types of job mobility, job changes within an industry and job changes across industries. It is hypothesized that a portion of human capital is industry-specific, and hence transferable across firms when a worker changes jobs within the same industry. This implies that a worker favors a job change within an industry to a job change across industries since he expects better outside wage offers in his current industry than in other industries, and that this is more so for a worker with longer industry tenure.

This paper uses the framework of duration model to investigate the effect of industry tenure on the two types of job changes. Estimation results reveal that industry tenure raises intra-industry mobility, but lowers inter-industry mobility. These findings strongly support the importance of industry-specific human capital.

This paper is organized as follows. Section 2 presents the competing risks hazard model specification. Section 3 describes the data drawn from the Survey of Income and Program Participation. Section 4 contains an analysis of nonparametric sample hazard function estimates and the estimation results of the competing risks specification. Concluding remarks are found in section 5.

II. Empirical Specification

Under the training theory, a worker accumulates job-specific human capital while employed, leading to a positive relationship between productivity and job tenure. If human capital has an industry-specific component as well, then the same argument applies to the relationship between productivity and industry tenure. That is, a worker who has been in a given industry longer is equipped with a larger stock of industry-specific human capital and hence more productive at his current industry than a comparable worker with less industry tenure.

This implies in terms of search theory (see for example Lippman and McCall (1976a, 1976b)) that the distribution of outside wage offers a worker faces in his current industry is better than that in other industries. It then follows that industry tenure makes a worker more likely to change jobs within an industry than across industries. The resulting statistical model of job duration is a competing risks model, where job spells can end at either intra- or inter-industry job chnages.[1]

Utilizing the proportional hazard model of Cox (1972), the two type-specific hazards of the Weibull specification for a worker with job tenure t and a vector of covariates x are given by

$$(1)\quad \lambda_q(t, x) = \alpha_q t^{\alpha_q - 1} \exp(x' \beta_q), \quad q = 1 \text{ or } 2,$$

where q denotes intra- and inter-industry movements.

Assuming that the distributions of the two types of completed spells are independent, the hazard of completing a spell is simply the sum of the two type-specific hazards:

1) For a detailed discussion of duration model, see Kalbfleisch and Prentice(1980), Lawless(1982), and Cox and Oakes(1985). Kiefer(1988) provides an excellent review of the duration model literature.

$\lambda(t, x) = \lambda_1(t, x) + \lambda_2(t, x)$. The survivor function, the probability of a job spell T_i for an individual i lasting to at least t_i, hence is given by

$$(2)\ S(t_i, x_i) = \Pr(T_i \geq t_i \mid x_i)$$
$$= \exp\left[-\int_0^{t_i} \lambda(u, x_i)\,du\right]$$
$$= \exp\left[-\int_0^{t_i} \{\lambda_1(u, x_i) + \lambda_2(u, x_i)\}du\right]$$
$$= \exp\left[-\{\Lambda_1(t_i, x_i) + \Lambda_2(t_i, x_i)\}\right]$$

where $\Lambda q(\cdot)$, q=1,2, denote integrated hazard functions. The log-likelihood function for a sample of n spells is

$$(3)\ L(\theta) = \sum_{i=1}^{n}\left[d_{1i}\ln f_1(t_i, x_i, \theta) + d_{2i}\ln f_2(t_i, x_i, \theta) + (1-d_{1i}-d_{2i})\ln S(t_i, x_i, \theta)\right]$$
$$= \sum_{i=1}^{n}\left[d_{1i}\ln\lambda_1(t_i, x_i, \theta) + d_{2i}\ln\lambda_2(t_i, x_i, \theta) + \ln S(t_i, x_i, \theta)\right]$$

where $d_{1i} = 1$ if spell i ends with an intra-industry movement, 0 otherwise, d_{2i} is defined similarly for an inter-industry movement, and f_i, i=1,2, denote density functions. Noting $\Lambda q(t_i, x_i) = \exp(x_i'\beta_q)\, t_i^{\alpha_q}$, q = 1,2, in Weibull specification and using (1) and (2), the Weibull specification of (3), to be estimated later in this paper, can be written as

$$(4)\ L(\alpha_1, \beta_1, \alpha_2, \beta_2)$$
$$= \sum_{i=1}^{n}\left\{d_{1i}\left[x_i\beta_1 + \ln\alpha_1 + (\alpha_1 - 1)\ln t_i\right] - \exp(x_i\beta_1)t_i^{\alpha_1}\right\}$$
$$+ \sum_{i=1}^{n}\left\{d_{2i}\left[x_i\beta_2 + \ln\alpha_2 + (\alpha_2 - 1)\ln t_i\right] - \exp(x_i\beta_2)t_i^{\alpha_2}\right\}.$$ [2]

2) The same competing risks Weibull specification is used by Katz(1986), who envisages that workers on temporary layoff face competing risks of finding a new job and being recalled.

Ⅲ. Data

The data come from the 1984 panel of the Survey of Income and Program Participation (SIPP). SIPP is a multi-panel longitudinal survey conducted by the Bureau of the Census. The 1984 panel is the first panel of SIPP, and was initiated in October 1983 for over 60,000 people 15 years old and over in about 20,000 households in the United States.[3] The subsequent interviews are taken at a four-month interval, and in each interview information about the four calendar months preceding the interview is collected for all adults in sampled households. The four calendar months preceding each interview is called a reference period, and each round of interviews is referred to as a wave. Adults in the 1984 panel are interviewed for up to nine waves, thus providing data for to 36 months. The reference periods covered run from June 1983 through July 1986.'

SIPP collects information on labor force status and, for those who report employment during the four-month reference period, information on their jobs. Information on jobs includes employer identification number, industry and occupation, usual hours worked per week, wage rate and/or income in each month from each job, and starting/ending date if the respondent did not work the whole reference period at the jobs.

SIPP also contains information on the education and work history of adults in sampled households. This set of information on prior work history, collected in wave 3, makes SIPP well suited to a study of labor market dynamics. Since information on jobs held in the past is required for this study, only data on wave 3 and thereafter are used in the analysis.

For the empirical analysis of industrial job changes, two major decisions need to be made. They are the choices of the time unit of analysis and industry classification. A four-month period is chosen as the time unit. This choice is made in part for the practical reason that data are collected over the four-month-long reference periods. In addition, the four-month period is thought to be a reasonable choice for the analysis of job mobility of young workers. It is superior to a 12-month period, the most common choice in

3) The selection of households into the survey was done according to a sample secection methodology similar to that used for the Current Population Survey.

previous studies, since job changes involving jobs that last for up to 12 months may be omitted when mobility is defined over a one-year period. At the same time, a period of four months appears to be reasonably long enough for workers to make their decisions on job changes.

Some discussion about the treatment of multiple job holders is in order. A multiple job holder is observed if a worker holds more than one job concurrently or if the worker changes jobs within a four-month-long reference period. In this analysis, multiple job holders in any period are assigned their most important job in that period. The most important job is defined as the one worked the most days during the period.[4]

For the industry classification, the three-digit codes of the 1980 Census of Population Industry Classification System are used to group jobs into 14 major industries. For the list of these industries and the 1980 census industry classification codes, see Appendix 1.

The sample used in the analysis is restricted to male employees who are aged between 21 and 30 as of the end of wave 3 of SIPP. Young workers are chosen since they are more mobile than older workers (See for example Mincer and Jovanovic (1981)). The choice is desirable since a relatively high frequency of job changes among these workers will give more reliable estimates of job mobility. The exclusion of people below 21 is dictated since the questions on prior work history were asked only to those aged 21 and over as of wave 3 of SIPP.

Also excluded from the analysis are those who were enrolled in postsecondary school at any period during or after wave 3 of the survey. Affected by this exclusion are those who, while in the sample, attend postsecondary school and those who enter (or reenter) college or university after some period of employment. This exclusion is desirable for an analytical purpose, since most jobs held by those who are in school either currently or in the near future are intrinsically temporary, and hence exits from these jobs are likely to be governed differently than movements from more regular jobs held after leaving school.

To focus on interfirm mobility, one more condition is imposed for the inclusion in the estimation: A worker should continue to work for wage or salary in the immediately sub

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4) This means that jobs which last for up to four months may be omitted from the analysis. For example, if a spell of a job, which lasts no more than four months, lies evenly divided across two periods, then in each of the two periods, the job may be determined as "unimportant" and hence can be ignored.

sequent period to be counted as a valid case in any period.[5] This condition may not be satisfied for two reasons. First, individuals can be dropped in later waves from the survey due to either sample reductions made by the Bureau of the Census for budgeting purposes, or sample attritions.[6] Second, some workers can make a transition into self-employment, (long-term) unemployment, or nonparticipation.

The selection criteria stated above are met by 1400 male workers as of the end of wave 3. These workers are considered as being at the risk of changing jobs across waves, and they are followed through wave 9 unless they leave the sample or make a transition to states other than paid employment before the completion of the survey. Of the total of 1400 workers in the sample, 406 workers (29. 0%) experience at least one job change during the up-to-two-year-long interval, and 181 workers (12. 9%) change their jobs more than once during the interval.[7] See table 1 for the distribution of workers by frequency of job changes.

The unit of observation in this analysis is the job spell (measured in four-month-long periods). Workers who change their jobs during the observation period provide multiple job spells, and hence the total number of job spells is larger than the number of individuals included in the sample. For the purpose of estimation, it is assumed that multiple spells for the same person are independent. It is also assumed that censoring, both left- and right-, is independent of a job change, the event of interest in this analysis.

In this paper, jobs are grouped into two sectors, a manufacturing sector and a non-manufacturing sector. Jobs belonging to industries 1 through 5 (see Appendix 1) make the manufacturing sector and jobs in the rest of industries are grouped together to form the non-manufacturing or service sector, and empirical analyses are performed for

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5) To further ensure that workers who experience long-term nonemployment are excluded from the analysis, an individual who worked less than four weeks at his job during a four-month-long reference period is treated as not working in that period.

6) for example, eighteen percent of the sample was deliberately eliminated after the fourth interview.

7) Taking into account the fact that some workers are dropped from the sample in the middle of the survey and hence not followed thereafter, the proportion of workers who change jobs at least once during the two-year period rises to about 44%. This proportion is in accordance with those reported by Mincer and Jovanovic (1981), who analyze job changes over a two-year period. Their sample includes those who experience a spell of unemployment between jobs, and they report that the proportions of movers are 47% and 12% for male workers with working experience of less than 4 years, and over 25 years, respectively.

each of the two sectors. This is done to allow for the possibility that the mechanisms governing mobility behaviors in the two sectors may be different.

Also, to control for possible differences across occupations in job mobility, occupation dummies constructed using one-digit occupation codes of the 1980 Census of Population Occupation Classification System are included in the estimation. They are: 1) Managerial and Professional, 2) Technical, Sales, and Administrative, 3) Service, 4) Farming, Forestry, and Fishing, 5) Precision production, Craft, and Repair, and 6) Operators, Fabricators, and Laborers.[8)]

Definitions of variables are given in Appendix 2. For the calculation of the values of prior-work-related variables such as industry tenure and general experience as of the start of a job, information on prior history mentioned above is used.

Another variable to be mentioned is the starting hourly wage rate at the job. For left-censored spells, starting wage is not observed, and hence is computed by discounting the observed later-period wage rates. The uniform per-period discount rates used are .020 and .025 for the manufacturing and service sectors, respectively.[9)] These discount rates are chosen on the basis of the average across-period wage growth rate of stayers in corresponding sectors.

Summary statistics by type of spells of variables used in the estimation for the two sectors are presented in tables 2a and 2b. There are 814 job spells in the manufacturing sector and 1085 spells in the service sector. In the manufacturing sector, 22.5 percent of the spells complete at intra-industry mobility, and 11.1 percent complete at inter-industry mobility. The corresponding proportions in the service sector are 21.6 percent and 16.4 percent, respectively.

Not surprisingly, in both sectors, the average duration of completed spells, both intra- and inter-industry, is shorter than the average duration of censored spells. In the manufacturing sector, for example, both types of completed job spells last on average less than two years before they are terminated, while the average observed duration of censored spells is longer than four years.

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8) In the estimations, occupation categories 3), 4), and 6) are to be treated collectively as the reference category.

9) This procedure may result in overestimating the starting wage of stayers compared to that of movers, since, other things being equal, it is likely that stayers have enjoyed higher inside-firm wage growth than movers.

A comparison of starting industry tenure between the two types of completed spells, spells ending at intra-industry mobility and spells ending at inter-industry mobility, indicates that workers who later choose an intra-industry job change are those who on average stayed longer in their industry by the time they start their current jobs than workers who later choose an inter-industry job change. This suggests the importance of industry-specific components of one's productivity.

Ⅳ. Sample Hazard Functions and Estimation Results

Before presenting parametric estimation results of competing risks models of job mobility, we discuss the Kaplan-Meier (non-parametric) sample hazard functions. The usual single-risk Kaplan-Meier estimator is modified to define type-specific hazard function estimators. That is, when there are two different ways of ending a spell, type-specific hazard functions, $\lambda_q(t_j)$, q = 1 or 2, can be estimated by

$$(5)\ \lambda_q(t_j) = \frac{n_j^q}{R_j}$$

where n_j^q is the number of spells that are completed with cause q during interval j and R_j is the number at risk at duration j. Tables 3a and 3b display the hazard function estimates, based on the Kaplan-Meier estimator of the two types of job mobility in the two sectors.

Although the longest observed duration in the manufacturing and service sectors are 44 and 46 periods respectively, no job spells with observed duration of 34 periods or longer terminate with either type of job changes (the only exception is the longest spell in the service sector, which completes at inter-industry mobility). Tables 3a and 3b thus contain information on the first 36 periods only.

The estimates of the two type-specific hazards in the two sectors are plotted in figures 1a and 1b.[10] Comparing the two sectors, both intra- and inter-industry hazard rates are

10) Note that the intra – and inter – industry hazard rates for the longest observed duration in the service sector (46periods), which are estimated at 0 and 1, are not shown in figure 1b.

higher in the service sector than in the manufacturing sector at almost all levels of job tenure. Figures 1a and 1b also reveal that the relative odds of intra-industry job changes to inter-industry job changes are higher in the manufacturing sector than in the service sector. In the manufacturing sector, the average hazard rate of intra-industry mobility is approximately twice as high as that of inter-industry mobility. In the service sector, in contrast, the two type-specific hazard rates are relatively close. This might suggest that industry-specific human capital is more valuable in the manufacturing sector than in the service sector.

For duration dependence, except for the fact that the hazard rate of each type of job mobility falls drastically during the first year (the first three periods) at a job, no clear pattern of duration dependence is shown in either sector. This can also be seen in figures 2a and 2b, which depict the two type-specific integrated hazards together with the survivor rate in the manufacturing and service sectors, respectively. If we ignore the first few periods, in both sectors, the integrated hazard for each of the two types of mobility is close to a straight line, which implies a constant hazard rate. With the initial periods included, however, the two type-specific integrated hazards are moderately concave in both sectors, which implies a slightly decreasing hazard or negative duration dependence.

Finally, the survivor rates shown in figures 2a and 2b indicate that jobs in the manufacturing sector are more likely to last than jobs in the service sector (see also tables 3a and 3b). For example, in the manufacturing sector, the proportion of jobs that last up to ten years (30 periods) is 53 percent, while the corresponding proportion in the service sector is 44 percent.

We now turn to parametric estimations of the proportional hazard competing risks models. In the estimations, we ignore unobserved heterogeneity, with the understanding that heterogeneity leads to a downward-biased estimate of duration dependence.[11)]

Maximum likelihood estimates of (4) in section 2 for the manufacturing and service sectors are presented in tables 4a and 4b. The second specification of each table is different from the first one in that the former additionally controls for (imputed) starting wage. Only time-invariant covariates are included in the estimation.[12)]

11) Heckman and Singer(1984) provide a detailed discussion on potential problems that arise when individual heterogeneity is ignored in duration model estimations. They suggest a nonparametric maximum-likelihood estimator.

Estimation results indicate that, in both sectors, initial industry tenure raises the hazard of intra-industry mobility, but lowers the hazard of inter-industry mobility, although its effect on the hazard of inter-industry mobility in the service sector is not statistically significant at conventional levels of significance. The negative effect of starting industry tenure on inter-industry mobility is strong evidence of the presence of industry-specific components of one's productivity.

The positive effect of starting industry tenure on intra-industry mobility, which indicates a higher risk of quitting a job to take a new job in the same industry, is unexpected. This might suggest that industry tenure has more favorable impact on outside wage offers (from the same industry) than on inside wage offers, which may be due to the dominance of job tenure over industry tenure in the determination of inside-firm wage rates.

General experience at the start of a job, in contrast, has a strong positive impact on both types of hazards in both sectors. This may reflect a relatively high innate propensity to move of those with longer initial experience (initial experience of those who never moved before is by definition zero). Alternatively, this may suggest that job search intensity rises for the first few years in the labor market, and hence may not apply to older workers.

For duration dependence, the data exhibit weak negative duration dependence in both intra- and inter-industry hazards in both sectors, although the hypothesis of a constant hazard rate cannot be rejected except for inter-industry mobility in the service sector. Negative duration dependence can be due to the positive effect of job tenure on wage and fringe benefits. Recall, however, that unmeasured heterogeneity, which is ignored in this analysis, can also lead to a spurious negative duration dependence through workers' self-selection in terms of their unobservable innate mobility.

Duration dependence among workers in this sample, implied by the estimated value of α, however, is not as strong as found in other studies. For example, Horowitz and

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12) It is possible, however, that one's occupation changes within the same job throuhg a promotion. Also, education, measured as the years of schooling as of the last period in the survery for each individual, can take different values during early periods (before the start of the survey) of left-censored spells, if a worker was enrolled in school while working during those periods (recall that those who are enrolled during the survey period are excluded from the sample).

Neumann (1987), who use the single-risk Weibull specification in analyzing job separation behavior of prime-aged male workers drawn from (the control group of) the Denver Income Maintenance Experiment, estimate α at around .69 with the standard error of .048.[13] Abraham and Farber (1987) also estimate the single-risk Weibull specification to impute completed durations of right-censored jobs held by male household heads aged 18-60 drawn from (the Survey Research Center Subsample of) the PSID. Their estimates of α are .380 and .394 for nonunion white-and blue-collar workers, respectively (with standard errors of .028 and .017), which implies even stronger negative duration dependence.

The degree of negative duration dependence found in this study is comparable to that of McCall (1990). McCall uses the single-risk Weibull specification for a sample of young workers (aged below 30), both male and female, drawn from the National Longitudinal Survey's youth cohort and gets an estimate of .871 with the standard error of .023. This suggests that the relatively weak negative duration dependence found both in this study and in McCall may be due to the fact that samples used in both studies are composed of young workers who are less self-selected in terms of their innate mobility and are in an early stage of their career during which the job search intensity may rise.

In both sectors, conditioning hazards on starting wage hardly affects duration dependence and the effects on hazards of other covariates including initial industry tenure. The effect of the starting wage itself on the two hazards varies across sectors. In the manufacturing sector, it is positive for the intra-industry hazard, but negative for the inter-industry hazard. In the service sector, in contrast, it raises both hazards, although its effect on the inter-industry hazard is not significant.

The strong positive effect of initial wage on the hazard of (intra-industry) mobility is at variance with the findings by others (e.g. McCall (1990), Topel (1986)), and no easy explanation can be found for this. McCall who does not distinguish between intra- and inter-industry job changes, for example, finds that the effect of initial hourly wages on job separation is significantly negative for all of his specifications, both parametric and

13) Horowitz and Neumann also try (semiparametric) quantile estimation. They find that the two methods yield similar results and conclude that the Weibull specification is acceptable at least for their sample in analyzing workers' job separation behavior.

semiparametric, including the Weibull specification.[14]

As a final check, another set of estimates are obtained using new job spells only. These spells start during the study period (waves 3 through 8 of the SIPP), and hence do not create problems due to left-censoring. The data set contains 666 new job spells. Due to a relatively small number of spells, estimation is done for all new spells without distinguishing between the manufacturing and service sectors. Table 5 presents the maximum-likelihood estimates of (4) for the new spells.

Comparing table 5 with tables 4a and 4b, the most noticeable difference is that, for new job spells, both types of job mobility hazard rise rather than fall as tenure progresses. This opposite effect of job duration on hazards may come from the fact that the workers involved are those who have experienced at least one job change before the start of their jobs analyzed here, and hence are different from average workers in their job changing behavior. Another possibility is that job mobility hazards actually rise during the initial couple of years at jobs (recall that the maximum duration of the new job spells is two years (six periods)) before they fall thereafter. This possibility is consistent with both worker-firm matching theory (Jovanovic (1979)) and search theory. The estimated effects of ınitial experience are also different from those shown in tables 4a and 4b. The effect of experience on the two types of hazards is virtually nil whereas experience was previously estimated to have a strong positive impact on both hazards.

In contrast, the effects of initial industry tenure shown in table 5 are very similar to those in tables 4a and 4b. That is, initial industry tenure raises the hazard of intra-industry mobility, but lowers substantially the hazard of inter-industry mobility. This finding reinforces the argument for the presence of industry-specific components of productivity. The estimated effects of starting wage are also similar to those obtained for all job spells. Job spells with a higher starting wage are more likely to terminate with a within-industry movement, but less likely to end with an across-industry movement. Its effect on the two types of mobility combined, however, seems negative, which agrees with the findings by others (e. g. McCall (1990), Topel (1986)).

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14) Tables 4a and 4b show that the effect of initial wage on the two types of mobility combined is, if anything, also positive rather than negative.

V. Conclusions

The human capital theory traditionally distinguishes between firm-specific human capital and general human capital. This paper has attempted to identify industry-specific components of a worker's productivity, which are transferable across jobs when a job change takes place within the same industry. This is done by investigating the effect of industry tenure on hazards of two types of job changes, job changes within an industry and job changes across industries.

Estimation results of the competing risks model for young male workers drawn from the SIPP indicate that industry tenure plays an important role in determining the type of job changes. Industry tenure raises the hazard rate of intra-industry mobility, but lowers the hazard rate of inter-industry mobility. This suggests that industry-specific human capital discourages a worker from switching to different industries, especially in the manufacturing sector, in the same way as job-specific human capital deters a worker from changing jobs. Moreover, the positive effect of industry tenure on intra-industry mobility suggests that industry-specific human capital has more favorable impact on outside wage offers from the same industry than on inside wage offers.

Another interesting finding in this analysis is that workers' mobility, generally known to decline with job tenure, may rise during early stages at jobs. Empirical estimates indicate that workers' mobility, both intra- and inter-industry, rises during the first couple of years at jobs before it declines eventually, suggesting that wage gains from search may be of considerable magnitude, at least for young workers.

Appendix 1 : Industry classification

Industry	Classification
1. Agriculture, Forestry, and Fisheries	010 - 031
2. Mining	040 - 050
3. Construction	060
4. Non-durable Goods Manufacturing	100 - 222
5. Durable Goods Manufacturing	230 - 392
6. Transportation, Communication, and Other Public Utilities	400 - 472
7. Wholesale Trade	500 - 571
8. Retail Trade	580 - 691
9. Finance, Insurance, and Real Estate	700 - 712
10. Business and Repair services	721 - 760
11. Personal Services	761 - 791
12. Entertainment and Recreational Services	800 - 802
13. Professional and Related Services	812 - 892
14. Public Administration	900 - 991

Appendix 2 : Variable definitions

Variables	Definitions
Demographic variables:	
NONWHITE	= 1 if nonwhite
EDUCATION	Years of schooling as of the end of SIPP
Work-related variables:	
ST_IND_TEN	Number of consecutive periods in current industry as of the start of the job
ST_EXPRNCE	Total number of periods in labor market as of the start of the job
ST_LNWAGE	Log of starting hourly wage
Occupation dummies:	
PROFESSIONAL	= 1 if Managerial and Professional job
TECHNICAL	= 1 if Technical, Sales, and Administrative job
PRODUCTION	= 1 if Precision production, Craft, and Repair job

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〈Table 1〉 Workers by frequency of job changes

Frequency of job changes (A)	No. of workers (B)	No. of job changes (C = A x B)
0	994	0
1	225	225
2	112	224
3	51	153
4	8	32
5	9	45
6	1	6
Total	1400	685

〈Table 2a〉 Summary statistics of job spells:Manufacturing

	Censored		Completed			
			within-industry		across-industry	
Sample size	541		183		90	
Variables	Mean	SD	Mean	SD	Mean	SD
Duration	13.37	10.82	5.20	6.39	5.39	6.57
NONWHITE	.091		.098		.122	
EDUCATION	12.23	2.20	12.23	1.87	12.17	1.89
ST_IND_TEN	2.20	4.83	4.59	7.04	2.06	4.99
ST_EXPRNCE	13.98	10.66	20.30	9.87	19.27	9.28
ST_LNWAGE	1.916	.44	2.013	.2	1.812	.57
PROFESSIONAL	.105		.077		.111	
TECHNICAL	.078		.038		.056	
PRODUCTION	.353		.464		.378	

〈Table 2b〉 Summary statistics of job spells: Service

	Censored		Completed			
			within-industry		across-industry	
Sample size	673		234		178	
Variables	Mean	SD	Mean	SD	Mean	SD
Duration	11.13	9.08	4.79	5.77	4.89	6.23
NONWHITE	.119		.120		.135	
EDUCATION	13.00	2.54	13.12	1.87	12.17	1.89
ST_IND_TEN	1.97	4.93	4.40	6.84	1.73	4.16
ST_EXPRNCE	13.91	10.85	18.86	11.38	17.19	9.99
ST_LNWAGE	1.791	.59	1.891	.58	1.803	.56
PROFESSIONAL	.195		.205		.174	
TECHNICAL	.279		.295		.174	
PRODUCTION	.141		.103		.163	

〈Table 3a〉 Sample hazard function estimates: Manufacturing sector

Duration	Workers at risk	Within-industry hazard	Across-industry hazard	Survivor rate	No. of spells censored
1	814	.085	.032	.883	51
2	668	.042	.024	.825	63
3	561	.021	.011	.799	29
4	514	.025	.019	.763	16
5	475	.019	.011	.740	3
6	458	.022	.017	.711	30
7	410	.010	.007	.699	20
8	383	.005	.005	.692	20
9	359	.008	.006	.682	14
10	340	.012	.000	.674	15
11	321	.000	.000	.674	14
12	307	.013	.007	.661	11
13	290	.017	.000	.650	14
14	271	.000	.000	.650	20
15	251	.016	.004	.637	10
16	236	.000	.004	.634	18
17	217	.005	.000	.631	25
18	191	.031	.005	.608	5
19	179	.006	.011	.598	13
20	163	.012	.000	.590	23
21	138	.007	.007	.582	8
22	128	.000	.008	.577	9
23	118	.000	.000	.577	11
24	107	.000	.009	.572	7
25	99	.010	.000	.566	9
26	89	.000	.000	.566	9
27	80	.000	.000	.566	5
28	75	.013	.000	.559	4
29	70	.000	.000	.559	9
30	61	.033	.016	.531	5
31	53	.019	.000	.521	2
32	50	.000	.000	.521	6
33	44	.000	.023	.509	4
34	39	.000	.000	.509	5
35	34	.000	.000	.509	14
36	20	.000	.000	.509	2

〈Table 3b〉 Sample hazard function estimates: Service sector

Duration	Workers at risk	Within-industry hazard	Across-industry hazard	Survivor rate	No. of spells censored
1	1085	.076	.070	.853	60
2	866	.039	.023	.800	75
3	737	.037	.016	.758	56
4	642	.025	.012	.730	31
5	587	.022	.014	.703	7
6	559	.029	.027	.664	27
7	501	.000	.012	.656	36
8	459	.013	.004	.645	29
9	422	.012	.005	.634	20
10	395	.008	.005	.626	24
11	366	.005	.011	.616	25
12	335	.015	.009	.601	18
13	309	.013	.013	.585	28
14	273	.004	.000	.584	42
15	230	.013	.022	.563	19
16	203	.010	.005	.555	16
17	184	.000	.005	.552	17
18	166	.018	.006	.539	12
19	150	.000	.007	.535	16
20	133	.000	.000	.535	18
21	115	.017	.017	.516	9
22	102	.049	.010	.486	6
23	90	.000	.011	.481	13
24	76	.026	.000	.468	5
25	69	.000	.029	.454	4
26	63	.000	.000	.454	10
27	53	.000	.000	.454	4
28	49	.000	.000	.454	4
29	45	.000	.000	.454	4
30	41	.024	.000	.443	3
31	37	.000	.000	.443	2
32	35	.000	.000	.443	6
33	29	.034	.000	.428	3
34	25	.000	.000	.428	6
35	19	.000	.000	.428	10
36	9	.000	.000	.428	1

〈Table 4a〉 Competing risks Weibull model: Manufacturing sector

	(1)		(2)	
	within-industry hazard	across-industry hazard	within-industry hazard	across-industry hazard
ALPHA	.906	.911	.920	.901
	(.080)	(.111)	(.081)	(.114)
CONSTANT	-5.37	-5.34	-6.03	-4.96
	(.554)	(.870)	(.635)	(.878)
NONWHITE	.117	.398	.203	.349
	(.259)	(.351)	(.263)	(.349)
EDUCATION	.035	-.019	.006	.016
	(.040)	(.061)	(.012)	(.064)
ST_IND_TEN	.029	-.044	.027	-.043
	(.012)	(.022)	(.012)	(.022)
ST_EXPRNCE	.084	.092	.080	.096
	(.009)	(.013)	(.009)	(.013)
ST_LNWAGE	-	-	.570	-.482
	-	-	(.194)	(.220)
PROFESSIONAL	-.511	-.140	-.679	-.077
	(.307)	(.366)	(.308)	(.359)
TECHNICAL	-.580	-.332	-.629	-.292
	(.406)	(.498)	(.411)	(.502)
PRODUCTION	.240	-.035	.132	.046
	(.154)	(.240)	(.159)	(.242)

Numbers in parentheses are standard errors.
The number of observations is 814.

〈Table 4b〉 Competing risks Weibull model: Service sector

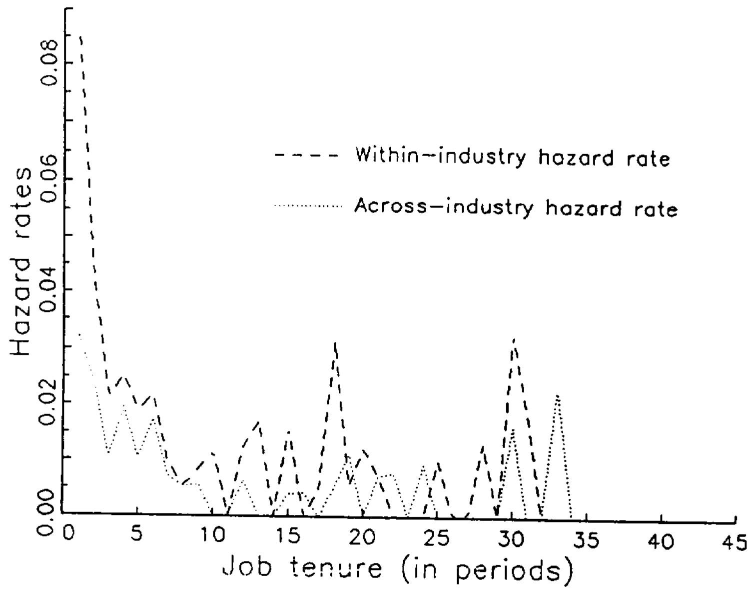
	(1)		(2)	
	within-industry hazard	across-industry hazard	within-industry hazard	across-industry hazard
ALPHA	.908	.823	.919	.827
	(.071)	(.080)	(.072)	(.080)
CONSTANT	-4.82	-4.49	-5.13	-4.64
	(.477)	(.514)	(.495)	(.544)
NONWHITE	.198	.249	.250	.273
	(.192)	(.217)	(.196)	(.218)
EDUCATION	.036	.031	.020	.026
	(.032)	(.036)	(.033)	(.036)
ST_IND_TEN	.055	-.021	.055	-.021
	(.009)	(.018)	(.010)	(.018)
ST_EXPRNCE	.057	.057	.053	.055
	(.007)	(.008)	(.007)	(.008)
ST_LNWAGE	-	-	.316	.144
	-	-	(.123)	(.149)
PROFESSIONAL	-.155	-.403	-.196	-.432
	(.209)	(.240)	(.210)	(.243)
TECHNICAL	-.008	-.707	-.044	-.727
	(.163)	(.213)	(.165)	(.214)
PRODUCTION	-.411	-.075	-.430	-.091
	(.227)	(.212)	(.229)	(.215)

Numbers in parentheses are standard errors.
The number of observations is 1085.

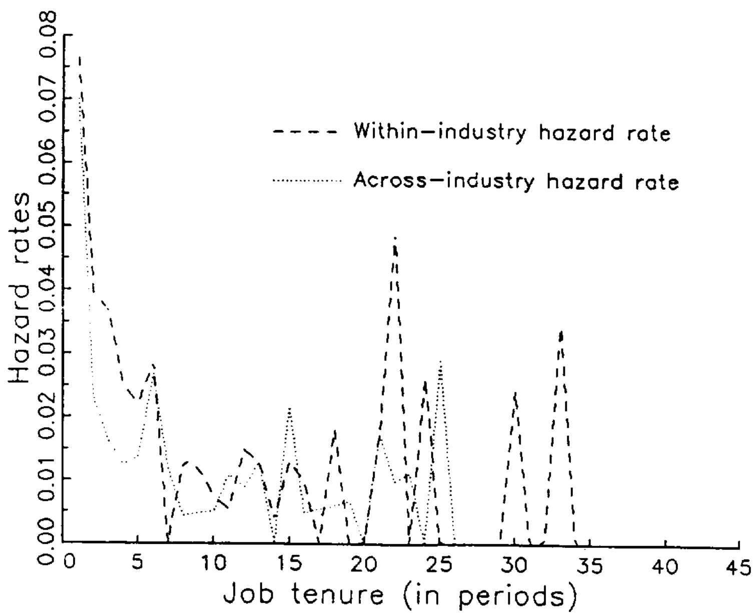
〈Table 5〉 Competing risks Weibull model: New job spells

	mean value	within-industry hazard	across-industry hazard
ALPHA		1.698	1.598
		(.123)	(.161)
CONSTANT		-2.56	-.699
		(.485)	(.537)
NONWHITE	.119	.081	.117
		(.216)	(.230)
EDUCATION	12.7	-.032	-.052
		(.032)	(.036)
ST_IND_TEN	4.83	.026	-.053
		(.008)	(.015)
ST_EXPRNCE	22.7	.000	.000
		(.007)	(.009)
ST_LNWAGE	1.93	.351	-.538
		(.141)	(.181)
PROFESSIONAL	.141	-.051	.228
		(.233)	(.265)
TECHNICAL	.159	-.053	-.175
		(.186)	(.248)
PRODUCTION	.266	-.086	-.085
		(.150)	(.210)

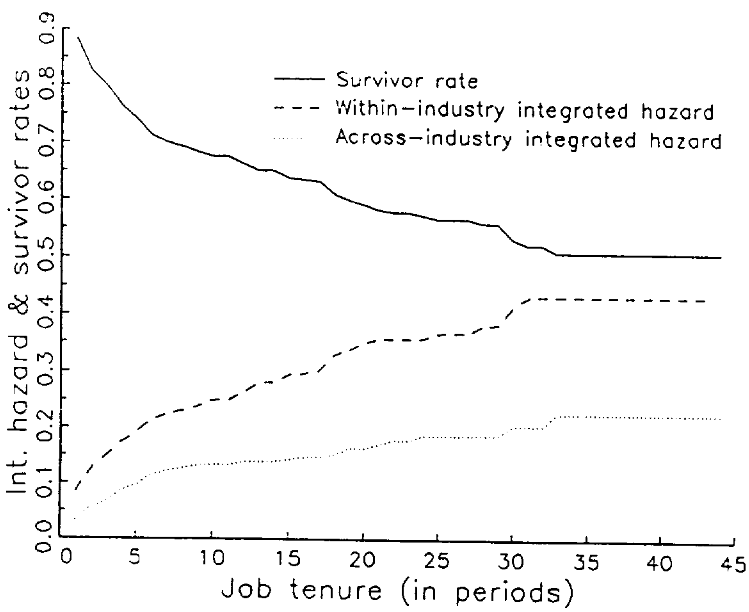
Numbers in parentheses are standard errors.
The number of observations is 666.



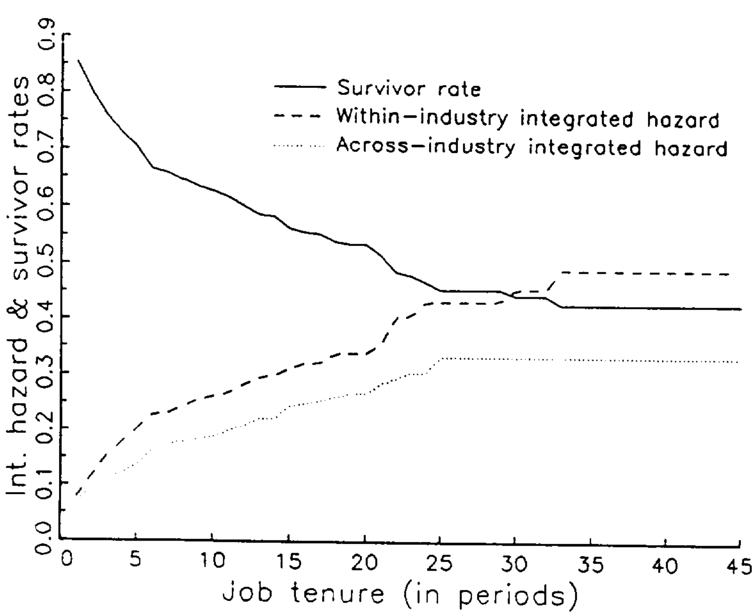
〈Figure 1a〉 Hazard rates: Manufacturing sector



〈Figure 1b〉 Hazard rates: Service sector



〈Figure 2a〉 Related rates: Manufacturing sector



〈Figure 2b〉 Related rates: Service sector