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Abstract: Although many studies have examined whether job stability and security have declined over time, the role of technology in job turnover has received little attention. This analysis examines the relationship between the likelihood that a worker remains at the same job for two years and various measures of technology usage across industries. Using data from the National Longitudinal Survey of Youth over 1980–98, the results indicate that the relationship between job retention and technology varies across measures of technology. Almost all of the relationship between job retention likelihoods and technology is due to quits, not to involuntary job loss. The results suggest that the relationship between technology, quits, and involuntary job loss differs between college graduates and less-educated workers.

JEL classification: J63, O33

Key words: technology, job turnover, quits, involuntary job loss

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Technology and Job Retention Among Young Adults, 1980-98

1. Introduction

The belief that job security has declined in recent years is widespread in the United States. During the 1990s, workers' expectations about the likelihood of keeping their job and the ease of finding another job were lower than during similar points in the business cycle in the 1970s and 1980s (Schmidt, 1999). Increased use of technology may partially underlie this concern that job security has declined, as feelings of job insecurity appear to have risen over time among workers in computer-intensive industries relative to other workers (Aaronson and Sullivan, 1998).

However, research by economists provides mixed support for the belief than job security has declined. Although studies have found some evidence consistent with falling median job tenure and retention rates, such declines appear modest and gradual for most demographic groups (Farber, 1998; Diebold, Neumark and Polsky, 1997; Neumark, Polsky and Hansen, 1999). Trends in involuntary job loss also suggest at most a modest decline in job security in the 1980s and 1990s for most workers (Gottschalk and Moffitt, 1999). Displacement rates in the mid-1990s were higher than during similar points in the business cycle in the 1980s but have since declined (Rodriguez and Zavodny, 2000). The largest declines in job stability and job security appear to have occurred among older men, including an increase in displacement rates among more educated men (Farber, 1997; Jaeger and Stevens, 1999).

Although the effect of technology on wages and wage inequality has been widely investigated, the relationship between technology and turnover has received relatively little attention.[1] Two previous studies used data from the Displaced Worker Supplements to the Current Population Survey to examine the relationship between measures of technology and involuntary job loss. Aaronson and Housinger (1999) find a positive association between the probability that a worker is displaced and some measures of technology usage in the worker's industry, such as computer investment and output per hour, and a negative relationship for other measures of technology, such as computer usage rates and total factor productivity. Addison, Fox and Ruhm (1996) similarly report a positive relationship between displacement and computer investment as a fraction of new investment across manufacturing industries.

This study examines the relationship between technology and job retention among young adults. Whereas previous research focused on displacement, which is involuntary job loss because of plant closure, job abolishment or insufficient work, this paper examines job stability, which encompasses quits and firings as well as layoffs. The role of technology in whether a young adult does not remain at the same job for two years because of an involuntary or voluntary separation is also examined. By using panel data on individuals, I am able to control for unobservable worker heterogeneity. Previous studies, in contrast, explored the relationship between technology and displacement using a cross-sectional approach. I also use several measures of technology to estimate the relationship between job retention and technology.

A finding that increased use of technology has lowered the likelihood that workers retain their jobs would have several potential implications. Job instability can lower wage growth, and the gains to changing jobs early in a career appear to have fallen over time (Bernhardt et al.,

[1] Studies of the relationship between technology and wages include Krueger (1993), who concludes that computer usage increases wages. In addition, increased use of computers appears to have increased the demand for skilled workers within industries and contributed to the increase in the return to education during the last two decades (Krueger, 1993; Autor, Katz and Krueger, 1998). However, the causality of such findings has been questioned (DiNardo and Pischke, 1997).

1999).[2] In addition, the implications differ if the effect on job retention occurs through firings and layoffs instead of through quits. Involuntary job loss is well known to result in substantial wage and hours losses and a period of unemployment for many workers (Farber, 1997).

The next section discusses why technology might affect job retention. The individual-level data, which are from the National Longitudinal Survey of Youth, the industry-level measures of technology and the estimation methodology are then explained, followed by a presentation of the results. The results indicate that relationship between technology and job retention varies across the measures of technology. Separating workers who do remain in the same job for two years into involuntary and voluntary job separations indicates that almost all of the estimated relationship is between job retention likelihoods and technology is due to quits, not to involuntary job loss. The relationship between technology, quits and involuntary job loss appears to differ between college graduates and less educated workers.

2. Theoretical background

The technological intensity of a firm is likely to affect the type of skills the firm demands in the labor market. Firms that utilize more technology tend to have higher skilled work forces than do less technology-intensive firms (Doms, Dunne and Troske, 1997). In addition, skill upgrading appears to occurs within industries as technological intensity increases, suggesting that increased use of technology changes the demand for skilled and unskilled labor (Berman, Bound and Griliches, 1994; Autor, Katz and Krueger, 1998).

Firms that use more technology may be less likely to retain workers for a given period of time than less technology-intensive employers. As Bartel and Sicherman (1999) note, firms that

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[2] Switching jobs can also increase wage growth, particularly if done in the early stages of a worker's career (Bartel and Borjas, 1981).

use more technology tend to have higher rates of technological change; technology-intensive firms tend to acquire new equipment and software more frequently than less technology-intensive firms.[3] If technology-intensive firms have higher rates of technological change, they may need to retrain workers in new job processes more frequently than other firms.[4] If it is less costly for a firm to hire new employees who are already familiar with the new technology than to retrain current workers, the firm may dismiss current employees. This hypothesis predicts that workers' job retention probabilities are negatively associated with measures of technology usage in their industry. In addition, the likelihood that job separation is involuntary may be positively associated with the measures of technology usage in an industry.

The relationship between technological change and job retention is likely to differ across workers with different skill levels. In particular, increased used of technology is likely to increase a firm's demand for skilled labor. This shift to a more technical work force may lead the firm to dismiss less educated workers relative to more educated workers. The relationship between technology and the probability that a worker remains in the same job over time is therefore is likely to be more negative among less educated workers than among more educated individuals.

Job retention probabilities reflect voluntary turnover as well as involuntary dismissals. Anecdotal reports suggest that quit rates tend to be higher in high-technology fields than in other fields; job hopping is notoriously common in Silicon Valley, for example. Job retention probabilities therefore could be lower in more technology-intensive industries because of voluntary turnover as well as because of firings and layoffs.

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[3] This analysis follows Bartel and Sicherman (1998, 1999) in using the terms technology usage, technological intensity and rate of technological change synonymously.

[4] Bartel and Sicherman (1998) find that technological change is generally positively associated with training among men employed in the manufacturing sector during 1987-92.

Alternatively, the measures of technological change may be positively associated with job retention if technological change boosts a firm's growth rate, causing it to be less likely to lay off workers. In addition, faster growth as a consequence of technological change may create more opportunities for advancement within a firm, which would increase retention rates by reducing quits. Measures of technology in an industry would then be positively associated with the probability that a worker remains in the same job during a given time period. These hypotheses are tested using data on whether workers retain their jobs for a 2-year period and technological intensity in workers' initial industry of employment.

3. Data description

3.1 Individual-level data

The individual-level data on job retention and workers' characteristics are from the National Longitudinal Survey of Youth (NLSY), a panel data set that began with a sample of 12,686 individuals aged 14-22 in 1979. The young adults were surveyed annually from 1979 to 1994 and every other year since 1994. The data set is useful for examining job stability because it covers participants during the early stages of their careers, when the majority of job changes take place and when long-term relationships with employers are established (Bernhardt et al., 1999). The NLSY is also suitable for examining the relationship between job stability and technology because it covers the period when personal computers and other forms of information technology became widely used in the work place.

Each wave of the NLSY includes data on up to five jobs a participant has held since the last interview.[5] Participants are asked if they reported any of these jobs in a previous interview,

[5] Internal promotions or lateral job moves with the same employer are recorded as the same job, so job and employer are used synonymously here and in the data set.

and the data set includes variables that allow for matching of employers across consecutive waves. The five employers include the current or most recent employer, also known as the "CPS employer." If a respondent holds two or more jobs at the time of the interview, the job with the most hours is considered the CPS employer. This analysis focuses on the CPS employer when examining whether a worker remained in the same job for a 2-year period.

The analysis examines 2-year job retention probabilities because the survey was conducted only every other year after 1994.[6] Up to nine non-overlapping 2-year intervals are observed per individual, beginning in 1980-82 and ending in 1996-98.

Using data from the NLSY work history data set, the 2-year retention probabilities are created as follows. For each 2-year interval, an individual is included in the sample if the individual was employed at the time of the survey, year t. If the individual was not currently employed at the time of the interview two years later, year $t+2$, the individual is considered to have not remained with the same employer. If the individual was employed at time $t+2$, the CPS employer at time $t+2$ is compared to the CPS employer at time t. If they are the same employer, the individual is considered to have remained in the same job for two years; if they are not the same employer, a job separation has occurred.[7] The 2-year retention rate is therefore the fraction of individuals employed at time t who work for the same employer at time $t+2$. Individuals who were not interviewed in year $t+2$ or who were self-employed or working without pay in year t are not included in the sample.

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[6] The interval between the interviews used to construct the data may be more or less than 24 months but is referred to here as two years (the average interval in the full and manufacturing samples is 24.3 months).
[7] During 1980-94, the CPS employer is matched across 1-year survey intervals. To have remained in the same job for two years, an individual's CPS employer must be the same at time $t+2$ as at time $t+1$ and the same at time $t+1$ as at time t.

Several other restrictions are made on the sample. Individuals under age 18 in year *t* are not included. Only individuals in the cross-sectional NLSY sample and minorities in the supplemental sample are included; economically disadvantaged whites in the supplemental sample and individuals in the military sample are dropped because the NLSY stopped following these individuals before 1998. Observations with incomplete responses for the variables used in this analysis are dropped. Of the 9,763 individuals in the original cross-sectional sample and the minority supplemental sample, 8,790 are included in this analysis at least once. Up to nine observations per person are possible, and the average person appears in the sample five times. The NLSY adjusted the sample weights each year to correct for attrition and nonresponse, and those weights are used in this analysis.[8]

Figure 1 shows the 2-year retention rates for the sample over time. The upward trend in the retention rate is not surprising given that the NLSY sample aged from their late teens and early 20s in 1980 to their 30s during by the end of the period. The detrended retention rate, from which a linear time trend was removed, tends to decline in the 1990s, consistent with the decline in job stability noted by Farber (1997, 1998). The mean 2-year retention rate for the sample is 0.526, slightly higher than the rate reported by Bernhardt et al. (1999) using data on white men in the NLSY from 1980-93.

A subsample of workers in the manufacturing sector is used in part of the analysis. This sample includes 8,839 individuals who worked in a manufacturing industry at time *t*. The average number of observations per person in the manufacturing sample is 2.7, which is lower than in the full sample because individuals move in and out of the manufacturing sector but

[8] Time-varying weights for each individual are used in the basic logit specifications reported in all tables. Time-invariant weights are used in the random effects logit specifications reported in Table 3; the weights are the 1979 NLSY weights. The results are similar if the observations are not weighted.

remain in the full sample. The average probability of remaining in the same job for a 2-year period among manufacturing workers is 61 percent, higher than among the full sample of workers. As Appendix Table 1 indicates, manufacturing workers have completed less schooling, on average, than other workers and differ slightly in several other characteristics from the full sample.

Among workers who do not remain in the same job for two years, job separations may be either voluntary or involuntary. The NLSY asks why an individual left a job for up to five jobs held since the last interview; these data are used to assess whether individuals who did not remain at the time *t* CPS job for two years quit or were discharged. Individuals who were laid off, whose plant closed, were fired, or had a program or seasonal job end are classified here as having an involuntary job separation. Individuals who quit because of pregnancy or family reasons or left for other reasons are classified as voluntary separations. The reason why individuals left the CPS job they held at time *t* was reported by 90 percent of individuals who did not remain at the same job. In the full sample, about 30 percent of separations are involuntary and 70 percent are voluntary. The fraction of separations that are involuntary is higher in the manufacturing sample (38 percent) because displacement rates are higher in the goods-producing sector than in the service sector (Kletzer, 1998).

3.2 Industry-level technology data

The technology measures used in this analysis are at the industry level because the NLSY does not contain information about technology usage by workers or their firms. Using industry-level measures of technology has the advantage of reducing several econometric problems that might arise if firm-specific technology measures were used. A firm may adjust its technology usage in response to worker turnover, creating endogeneity problems if a measure of the firm's technology usage is included in the econometric model. A firm's growth rate may affect both its acquisition of technology and its retention of workers, creating omitted variable bias if the firm's technology usage is controlled for but its growth rate is unavailable. Using industry-level measures of technology mitigates these problems.[9]

Several variables are used to measure technological intensity. Computer usage rates and employment of scientists and engineers as a fraction of total employment are used here as measures of technology for workers in all sectors. Research and development (R&D) expenditures as a fraction of sales, computer investment as a fraction of total new investment, and the annual growth rate of total factor productivity (TFP) are also used to measure technological intensity among workers in the manufacturing industry. This approach allows for an examination of the robustness of the results to alternative measures of technology.

Each variable captures slightly different aspects of technology usage. The computer usage and scientists and engineers variables measure how intensively technology is used in production processes and are in levels. The R&D and computer investment variables also measure inputs into production, but the data are flows instead of stocks. The TFP variable is an output-based measure and gives the rate of change in output that is not accounted for by labor, capital, and other conventional factors of production. Previous studies discuss the merits and limitations of each measure (Allen, 1996; Bartel and Sicherman, 1998, 1999; Aaronson and Housinger, 1999). Data sources are detailed in the Appendix.

[9] In addition, the analysis focuses on measures of technology at the beginning of each 2-year period instead of technology usage during or at the end of the period to reduce simultaneity problems. The estimation strategy used here can be regarded as a reduced form because industry technology measures could be used as instruments for a firm's technology usage in order to control for endogeneity bias.

The technology variables are generally measured at the 2-digit SIC code level, although a few industries are measured at the 3-digit level. The technology variables matched to the full NLSY sample encompass 45 industries, while the manufacturing sample includes 22 industries. The analysis focuses on time-varying measures of the technology variables, where the technology variables are measured as close as possible to the beginning of each 2-year job retention interval. Two time-invariant measures of the technology variables are used in some specifications to examine the robustness of the results to alternative measures: the simple average within an industry over the time period used to create the time-varying measures, and the value of each technology variable at the start of the time period within each industry.

Table 1 reports the sample means for the measures of technology. All of the measures of technology usage increased during the sample period, as the difference between the means of the beginning-of-period variables and the means of the time-varying and average-over-period variables suggests. The mean computer usage rate is slightly lower in the manufacturing sector than across all industries, while scientists and engineers make up a larger proportion of employment in manufacturing, on average, than across all industries.

Correlations between the different technology variables give an indication of whether the variables give similar measures of technological intensity. Table 2 reports the correlations between the time-varying technology variables within industries. No two variables are perfectly correlated, indicating that the variables capture different aspects of technology. The growth rate of total factor productivity, which is the only output-based measure used here, tends to be the most weakly correlated with the other measures of technology.

4. Empirical methodology

Logit models are used to examine the determinants of the likelihood that an individual remained in the same job over a 2-year period. Determinants of the likelihood that an individual remained in the same job include individual characteristics, economic conditions and technological intensity in a worker's industry. The basic logit model estimated here is

$$\Pr(Y_{ijt}=1 \mid X_{it}, E_{it}, T_{jt}) = f(X_{it}, E_{it}, T_{jt}), \tag{1}$$

where *i* indexes individuals, *j* indexes industries, *t* indexes 2-year time periods and *f* is the logit function. The likelihood that an individual who works in industry *j* remains in the same job for a 2-year period that starts at time *t* is a function of the person's time-varying characteristics (X_{it}), time-varying economic conditions in the person's area (E_{it}), and technology usage in industry *j* (T_{jt}).

Individual characteristics that are likely to affect job retention include such variables as age and education. Appendix Table 1 reports the individual characteristics that are included in the model, which are standard.[10] The variables include both actual years worked at the job an individual holds at the start of each 2-year period (tenure) and total years worked since an individual turned age 18 (total experience).[11] The regressions also include age squared, tenure squared, 8 of 9 occupation dummy variables and a constant. The proxy for economic conditions is an index created by the NLSY that measures the unemployment rate in an individual's local

[10] The regressions do not include wages, which are likely to be endogenous in a job retention equation, because no obvious instrument is available. Berhardt et al. (1999) use a similar approach.

[11] Part of total experience must be imputed for individuals who turned age 18 before 1978, when the NLSY work history data used to derive the variable begin. The imputed value of this unobserved work experience for an older individual is the average number of years worked in 1978 by individuals who turned age 18 in 1978 multiplied by the number of years that work history cannot be observed for the older individual.

area and ranges from 1 to 6, with higher values indicating higher unemployment rates. The technology measures are as discussed above, and only one technology measure is included per regression. The error terms are White-corrected for individual-specific heteroscedasticity.

Unobservable individual heterogeneity may be important if more-skilled individuals are both more likely to retain their jobs and to work in technology-intensive industries. In addition, if working in a technology-intensive firm requires or rewards investment in firm-specific skills, workers who are less likely to remain at the same job may choose to not work at technology-intensive firms because they would benefit less from acquiring specific skills than would individuals who are more likely to remain at the same employer; because only individuals who remain at the same job benefit from acquiring specific skills, workers would tend to sort into industries with different levels of technological intensity based on the likelihood they will remain at the same job. Such heterogeneity would result in an upward bias in the relationship between job retention and technology usage.

The robustness of the results to controlling for unobservable individual characteristics is investigated using an individual random effects logit model. The random effects model requires assuming that the individual-specific effects are independent of the other covariates. A conditional logit model could also be used to control for unobservable individual heterogeneity, but the model is not able to estimate coefficients for time-invariant variables. The conditional logit model also cannot include observations from individuals for whom the dependent variable does not vary, reducing the sample size by 22 percent in full sample and 44 percent in the manufacturing sample.[12] Results from conditional logit models, which are not shown here, were

[12] A logit model with individual fixed effects is not estimated because an average of only five observations per individual are available in the full sample, and the fixed effects estimator is known to cause bias in nonlinear models with short panels. The results of linear probability models are similar to those shown here. Including year dummy variables in the linear probability models generally increases the estimated coefficients on the technology variables

generally similar to the random effects models but had considerably larger standard errors because of the smaller sample size.

This analysis focuses on the cross-sectional variation in industry-level measures of technology instead of on changes in technology within industries over time because of concerns about measurement error in the technology variables. A negative relationship between technology usage and job retention suggests that workers are less likely to remain at the same job in industries with higher rates of technological change than in industries with lower rates of technological change, not that workers are less likely to remain in the same job as the rate of technological change increases for a given industry. Differencing the measures of technology to examine the effect of changes in technology usage within industries will exacerbate any measurement error present in the data. The use of a nonlinear model and panel data makes it difficult to correct for such measurement error because the correction requires knowing the error structure of the mismeasured variable (Kao and Schnell, 1987). In addition, the direction of the effect of measurement error in right-hand-side variables on estimated coefficients is indeterminate in nonlinear models.

Measurement error in the NLSY reports of workers' industry is also a concern because workers would then be assigned incorrect values of the technology variables. About 21 percent of workers who remain at the same job at year *t+2* have an industry code that places them in a different SIC code than at year *t*. It is not possible to estimate the extent of potential measurement error for workers who did not remain at the same job, and previous studies of the relationship between technology and displacement did not address measurement error in workers' reported industry because they used cross-sectional data. Dropping individuals who

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without reducing their significance levels; however, the estimated coefficients on the computer investment and TFP variables are no longer significant in the manufacturing sample when year fixed effects are included in linear remain at the same job but report being in a different industry generally has little effect on the results.[13]

A multinomial logit model is used to examine the relationship between technology usage, job retention, involuntary separations, and voluntary separations.[14] The model estimates the likelihood that a worker is laid off or fired and the likelihood that a worker quits, relative to the likelihood of remaining at the same job. The same variables used in the logit models for whether an individual remained at the same job are included in the multinomial logit model, which is estimated separately for each technology variable. The error terms are White-corrected for individual-specific heteroscedasticity, and observations are weighted using the NLSY sample weights at time *t*.

5. Results

5.1 Job retention likelihood

The determinants of the likelihood a worker remains in the same job for two years are first investigated using time-varying values of the technology variables in logit and random effects logit models. Table 3 reports the estimated coefficients for the technology variables. Each estimated coefficient reported in the table is from a separate regression.

The relationship between industry technological intensity and the likelihood that a worker remains in the same job for two years differs across the measures of technology. In the logit

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probability regressions.

[13] When individuals who remain at the same job but report different industry codes are dropped from the full and manufacturing samples, the relationship between the scientists and engineers variables and the left-hand-side variables is no longer statistically significant.

[14] The multinomial logit model requires assuming the independence of irrelevant alternatives (IIA). Hausman specification tests did not reject the IIA assumption when a multinomial logit model was used for each of the technology variables in the full and manufacturing samples. The p-value of the Chi-square statistic was above 85 percent in each Hausman test.

regressions reported in column (1), the computer usage rate and scientists and engineers as a fraction of employment are positively associated with job retention in both samples. In the manufacturing sample, the ratio of R&D expenditures to sales is positively associated with job retention, while computer investment as a fraction of all investment and the TPF growth rate are weakly negatively associated with the likelihood a worker remains at the same job. As column (2) shows, the technology coefficients are significant in the random effects specifications in the full sample but not in the manufacturing sample, which has considerably fewer observations per individual than does the full sample. Nevertheless, the magnitudes of the estimated coefficients are similar across both specifications for each technology variable.

These results accord with the findings of research on the relationship between technology usage and displacement. The positive relationship between retention likelihoods and computer usage is consistent with the negative relationship between displacement probabilities and computer usage found by Aaronson and Housinger (1999). The negative relationship between retention likelihoods and computer investment accords with the positive association between computer investment and displacement probabilities reported by Addison, Fox and Ruhm (1996) and Aaronson and Housinger.

The general robustness of the results to including random effects suggests that unobserved individual heterogeneity does not significantly bias the estimated relationship between technology and job retention. Studies of the relationship between technology and wages, in contrast, suggest that unobserved individual heterogeneity plays a large role in accounting for the positive correlation between earnings and technology usage (DiNardo and Pischke, 1997; Bartel and Sicherman, 1999). Because the results suggest that unobserved individual heterogeneity has relatively little effect on the estimated relationship between technology and job retention, results from logit models that do not include individual effects are presented in the remainder of the paper.

The estimated coefficients on the non-technology variables are standard. Appendix Table 2 reports the results for the other variables in the regressions with the computer usage rate variable for the full sample and the manufacturing sample. The logit model and the random effects logit model give similar results, with more experienced and longer tenure workers having a higher likelihood of remaining in the same job, for example. The estimated coefficients are generally opposite in sign to Bernhardt et al. (1999), who investigated the determinants of job separation among young men using a random effects logit model. The pattern of the coefficients is generally similar across the two samples.

Because the sample consists of young adults, many of the job separations observed in the sample may be unrelated to technological change and simply reflect individuals returning to school. The regressions were estimated among a subsample of individuals whose education was completed as the time of the survey and who might be regarded as permanently in the labor force; these individuals were not currently or subsequently enrolled in school, and their educational attainment did not change during subsequent survey waves. About 78 percent of observations in the full sample and 84 percent of observations in the manufacturing sample are from individuals who have completed their schooling. The results, which are not shown here, are similar to those reported in Table 3, with the computer usage, scientists and engineers and R&D-to-sales variables positively associated with the likelihood of job retention and the computer investment and TFP growth rate variables negatively associated with job retention.

Using other measures of the technology variables has little effect on the results. Table 4 reports the estimated relationship between the likelihood of job retention and the average value of the technology variables during the sample period and the value of the technology variables at the beginning of the period. The table also reproduces the results using the time-varying values and includes the derivatives of the slopes, evaluated at sample means, for ease of comparison across the various measures. The results are generally robust to the different measures of the technology variables, as the derivatives are similar across the three ways of measuring most of the technology variables. The likelihood that a worker remains in the same job appears slightly more positively associated with scientists and engineers as a fraction of total employment and the R&D-to-sales ratio if those variables are measured at the beginning of the sample period rather than contemporaneously or as the average during the sample period.

The results do not suggest that workers who are less educated, and presumably less skilled, are less likely than more educated workers to retain jobs in industries with higher rates of technological change. Table 5 reports the results of interacting the time-varying technology variables with a dummy variable for whether a worker has at least completed college; the logit regressions also include the technology variable, a full set of educational attainment dummy variables and the other variables used in the job retention model.[15] If anything, the results suggest that more educated workers are less likely than less educated workers to remain at the same job in more technology-intensive industries. In the full sample, workers who have completed college are significantly less likely than other workers to remain in the same job as computer usage rates increase across industries. Aaronson and Housinger (1999) similarly find that college graduates are more likely than less educated workers to be displaced as computer usage rates increase.

[15] Interactions of the technology variables with three of the four of the educational dummy variables (less than high school, high school, some college and college) revealed few differences among the first three groups, so results with only an interaction with the college dummy variable are shown here.

The relationship between technology and job retention can also be measured within industries instead of across industries. Including a full set of industry dummy variables in the regressions gives the average relationship between the likelihood of job retention and increases in technology within industries, controlling for the other variables. As discussed above, such estimates are difficult to interpret because any measurement error in the data is exacerbated. In results not shown here, none of the estimated coefficients on the technology variables is even marginally statistically significant when industry fixed effects are in included in the regressions, and many of the coefficients are the opposite sign of those reported in Table 3.

5.2 Reason for job separation

Technological intensity may have different effects on the likelihood that a worker experiences an involuntary job separation than on the likelihood that a worker voluntarily leaves a job during a 2-year period. If technological change increases the demand for skilled labor, for example, technology-intensive industries may dismiss or layoff more workers than less technology-intensive industries but have similar quit rates. Alternatively, if technology usage boosts firms' growth rates, both quits and involuntary separations might be negatively associated with technological intensity.

Table 6 reports the estimation results for the technology variables in the multinomial logit regressions. Each row in the table is from a separate regression, and Appendix Table 3 reports the results for the other variables in the computer usage rate regressions. The likelihood of involuntary job loss, relative to the likelihood of job retention, is generally not significantly associated with technology. In the full sample, the relationship between the computer usage rate and the likelihood that a worker experiences an involuntary job loss is negative, similar to Aaronson and Housinger's (1999) results for displacement.

The relationship between the likelihood of a voluntary job separation, relative to remaining at the same job, and technology varies across the measures of technology. For the computer usage, scientists and engineers, and R&D variables, the likelihood that a worker quits instead of remaining at the same job for two years is negatively associated with technological intensity. As in the job retention models, the results change when computer investment or TFP growth is used to measure technology, and voluntary turnover is positively related to those measures of technological intensity. The multinomial logit results are similar when only individuals who have completed their education are included in the sample.

Separating the sample into workers who do not remain at the same job because of involuntary versus voluntary job separation reveals that the relationship between job retention and technology is almost entirely due to the relationship between quits and technology. For each technology variable, the relationship between the likelihood of job retention and technology usage is the opposite of the relationship between the likelihood of voluntary job separation and technology usage. Except for the computer usage variable in the full sample, the relationship between the likelihood of involuntary job separation and the technology variables is insignificant or in the same direction as the relationship between the likelihood of job retention and the technology variables.

Some results suggest that more educated workers are less likely than less educated workers to be involuntarily separated from their job but more likely to quit as technology increases. Table 7 shows the results of including a variable that interacts the technology variable with an indicator variable for college graduates in the multinomial logit models.[16] College graduates tend to be less likely than other workers to experience an involuntary job separation and more likely to quit as the computer usage rate, the ratio of scientists and engineers to total employment, and the ratio of R&D expenditures to sales increases, although not all of the results are significant. However, college graduates appear to be more likely than less educated workers to experience an involuntary job separation as the TFP growth rate increases across industries.

6. Conclusion

Previous research has found mixed results on the relationship between the likelihood that a worker is displaced and various measures of technological intensity in the worker's industry. This analysis broadens the focus to examine the relationship between the likelihood of job retention, which includes quits and firings as well as displacements, and technology usage across industries. The results vary across the measures of technology used here, with some variables indicating that the likelihood of job retention is higher in more technology-intensive industries, while other variables suggest the opposite.

The estimated relationships between job retention and the technology measures appear to be primarily due to the relationship between quits and technology and not due to involuntary job loss. The analysis also suggests that the relationship between technology and job mobility differs between college graduates and less educated workers, with college graduates slightly more likely to more likely to quit jobs in technology-intensive industries than other workers.

[16] The regressions include the time-varying technology variable, its interaction with a college dummy variable, a full set of education dummy variables, and all of the other variables included in other regressions. Few differences were apparent between workers who did not finish high school, high school graduates, and workers who had some college education when the technology variables were interacted with three of the four education dummy variables.

Some of the results suggest that less educated workers may be more likely than college graduates to not remain in the same job for two years because of an involuntary job loss, but the findings are not conclusive. Because workers who are displaced tend to incur substantial costs, including a period of nonemployment and wages losses when reemployed, future research should further examine the relationship between job loss and technology among less educated workers. In addition, the data set used here begins in 1980, about the time that word processors and personal computers began being integrated into the work place. Use of earlier data would allow for an examination of whether trends in job turnover before personal computers mirrored trends after. Research using data on employment patterns over a longer time period and among a sample that includes older adults as well as young adults is needed to conclusively determine the relationship between technology and job turnover.

Appendix

The computer usage rate variable is from supplements to the Current Population Survey (CPS) in October 1984, 1989 and 1993. The variable is the fraction of workers aged 18 and older in an industry that use a computer at work. The 1984 data are matched to the NLSY data for the periods 1980-82 through 1986-88; the 1989 data are matched to the NLSY data for 1988-90 and 1992-94; and the 1993 data are matched to the NLSY data for 1994-96 and 1996-98. The average-over-period computer usage variable is the simple average of the 1984, 1989 and 1993 values for each industry, and the beginning-of-period computer usage variable is from the 1984 data.

Scientists and engineers as a fraction of total employment in an industry is calculated from the 1979-96 CPS outgoing rotations group data. Two-year moving averages ending in the first year of each 2-year NLSY period are matched to the NLSY data (1979-80 CPS data are matched to the NLSY data for 1980-82, for example). The fraction of workers in an industry over 1979-96 who are scientists and engineers is used as the average-over-period variable, and the 1979-80 fraction is the value of the beginning-of-period variable.

The research and development expenditures (excluding federal funds) as a fraction of sales data are from the National Science Foundation (various years). Two-year moving averages ending in the first year of each 2-year NLSY period are matched to the NLSY data. The simple average of the R&D to sales ratio during the period 1979-96 is used as the average-over-period variable, and the average of the 1979 and 1980 ratios is used as the beginning-of-period variable.

The computer investment as a fraction of new investment data are from the Census of Manufactures (COM), which is done every five years. The COM reports expenditures for new computers and peripheral data processing equipment and total expenditures for new machinery and equipment at the 4-digit SIC code level, and the data are aggregated up to the 2- or 3-digit SIC code level. The 1977 COM data are matched to the 1980-82 NLSY data; the 1982 COM data to the 1982-84 and 1984-86 NLSY data; the 1987 COM data to the 1986-88 to 1990-92 NLSY data; and the 1992 COM data to the 1992-94 to 1996-98 NLSY data. The simple average over the four Censuses is used as the average-over-period data for each industry, and the 1977 COM data are used as the beginning-of-period data.

The annual growth rate of total factor productivity data are from the National Bureau of Economic Research (NBER) and are described by Bartelsman and Gray (1996). The data are available at the 4-digit SIC code level for 1959-94 and are aggregated up to the 2-digit level using total employment as the weights. Two-year moving averages ending in the first year of each 2-year NLSY period are matched to the NLSY data; the average over 1993-94 is matched to the 1996-98 NLSY data as well as to the 1994-96 NLSY data. The simple average over 1979-94 is used as the average-over-period data for each industry, and the 1979-80 average is used as the beginning-of-period data.

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Table 1
Sample Means for Technology Variables

	Full Sample			Manufacturing Sample		
	Time-varying	Average	Beginning	Time-varying	Average	Beginning
Computer usage rate in industry	.346	.344	.248	.330	.332	.250
Scientists and engineers/total employment	.027	.028	.022	.052	.051	.042
R&D expenditures/sales				.025	.024	.019
Computer investment/total investment				.069	.057	.026
Total factor productivity growth rate				.009	.005	-.022

Note: Shown are weighted means for the measures of technology used in the analysis. The full sample includes 45 industries, and the manufacturing sample includes 22 industries. The time-varying measures differ within industries across 2-year periods, the average measures are a time-invariant simple average of the time-varying measures within industries, and the beginning measures are the earliest observation for each measure of technology within industries (see Appendix for details). The weights are the NLSY sample weights in the first year for each 2-year period.

Table 2
Correlations Between Measures of Technology

	Computer Usage Rate	Scientists & Engineers/ Total Employment	R&D/Sales	Computer Investment/ Total Investment
A. Full sample				
Scientists & engineers ratio	.540			
B. Manufacturing sample				
Scientists & engineers ratio	.771			
R&D/sales	.598	.677		
Computer investment ratio	.368	.204	.481	
Total factor productivity growth rate	.248	.045	.072	.153

Note: Shown are the correlations between the time-varying measures of technology for the 45 industries in the full sample and the 22 industries in the manufacturing sample. The correlations are based on the industry-level data (one observation per industry per period), not on the weighted sample means.

Table 3
Relationship between Time-Varying Measures of Technology and 2-Year Job Retention Likelihood

	Logit (1)	Random Effects Logit (2)
A. Full sample		
Computer usage rate	.896	.975
	(.078)	(.124)
Scientists and engineers/ total employment	2.568	2.713
	(.373)	(.577)
B. Manufacturing sample		
Computer usage rate	.432	.419
	(.198)	(.295)
Scientists and engineers/ total employment	1.238	1.200
	(.568)	(.847)
R&D/sales	2.596	2.574
	(1.298)	(1.884)
Computer investment/ total investment	-1.215	-1.297
	(.618)	(.916)
Total factor productivity growth rate	-2.085	-2.238
	(1.212)	(1.712)

Note: The dependent variable equals one if an individual is employed in the same job for two years and zero otherwise. Shown are the estimated logit coefficients, with standard errors in parentheses. The error terms in the logit model are White-corrected for individual-specific heteroscedasticity. Observations are weighted using the NLSY sample weights. The regressions also include the variables listed in Appendix Table 2, 8 occupation dummy variables and a constant. The technology variables vary over time within industries. The data include up to nine 2-year periods for each individual during 1980-98.

Table 4
Relationship between Different Measures of Technology and 2-Year Job Retention Likelihood

	Time-varying (1)	Average over Period (2)	Beginning of Period (3)
A. Full sample			
Computer usage rate	.896	1.013	.992
	(.078)	(.083)	(.095)
	[.223]	[.252]	[.247]
Scientists and engineers/ total employment	2.568	2.998	4.473
	(.373)	(.364)	(.507)
	[.639]	[.746]	[1.113]
B. Manufacturing sample			
Computer usage rate	.432	.553	.568
	(.198)	(.205)	(.224)
	[.101]	[.130]	[.133]
Scientists and engineers/ total employment	1.238	1.178	2.224
	(.568)	(.581)	(.797)
	[.290]	[.276]	[.521]
R&D/sales	2.596	3.473	5.360
	(1.298)	(1.342)	(1.644)
	[.608]	[.813]	[1.255]
Computer investment/ total investment	-1.215	-1.382	-2.106
	(.618)	(.823)	(1.218)
	[-.284]	[-.324]	[-.493]
Total factor productivity growth rate	-2.085	-2.830	-1.971
	(1.212)	(4.084)	(.889)
	[-.488]	[-.663]	[-.461]

Note: Shown are the estimated logit coefficients for measures of technology in logit regressions where the dependent variable equals one if an individual is employed in the same job for two years and zero otherwise. The regressions also include the variables listed in Appendix Table 2, 8 occupation dummy variables and a constant. White-corrected standard errors are in parentheses, and derivatives of the slopes evaluated at sample means are in brackets. Each coefficient is from a separate regression. Observations are weighted using the NLSY sample weights. The data include up to nine 2-year periods for each individual during 1980-98.

Table 5
Relationship between Technology and 2-Year Job Retention Likelihood, by Educational Attainment

	Technology Variable (1)	Tech Variable * College (2)
A. Full sample		
Computer usage rate	.974	-.350
	(.088)	(.172)
Scientists and engineers/ total employment	2.793	-.852
	(.431)	(.830)
B. Manufacturing sample		
Computer usage rate	.413	.112
	(.216)	(.495)
Scientists and engineers/	.967	1.352
	(.622)	(1.484)
R&D/sales	2.074	2.608
	(1.445)	(3.274)
Computer investment/ total investment	-.803	-1.927
	(.677)	(1.509)
Total factor productivity growth rate	-1.135	-5.861
	(1.299)	(3.408)

Note: Shown are the estimated logit coefficients for measures of technology in logit regressions where the dependent variable equals one if an individual is employed in the same job for two years and zero otherwise. The regressions also include the variables listed in Appendix Table 2, 8 occupation dummy variables and a constant. White-corrected standard errors are in parentheses. Each row is from a separate regression. Observations are weighted using the NLSY sample weights.

Table 6
Relationship between Technology and Likelihood of Involuntary or Voluntary Job Separation Instead of Job Retention, Multinomial Logit Models

	Involuntary Separation (1)	Voluntary Separation (2)
A. Full sample		
Computer usage rate	-.834	-.954
	(.124)	(.088)
Scientists and engineers/ total employment	.347	-3.370
	(.542)	(.451)
B. Manufacturing sample		
Computer usage rate	.354	-.859
	(.290)	(.243)
Scientists and engineers/ total employment	1.534	-2.696
	(.783)	(.738)
R&D/sales	1.822	-5.205
	(1.795)	(1.600)
Computer investment/ total investment	1.250	1.454
	(.865)	(.742)
Total factor productivity growth rate	-.702	4.123
	(1.708)	(1.422)

Note: Shown are the estimated coefficients for measures of technology in multinomial logit regressions, where remaining at the same job for two years is the omitted category. The regressions also include the variables listed in Appendix Table 3, 8 occupation dummy variables and a constant. The technology variables vary over time within industries. White-corrected standard errors are in parentheses. Each row is from a separate regression. Observations are weighted using the NLSY sample weights.

Table 7
Technology and Likelihood of Involuntary or Voluntary Job Separation Instead of Job Retention, by Educational Attainment, Multinomial Logit Models

	Involuntary (1)	Involuntary * College (2)	Voluntary (3)	Voluntary * College (4)
A. Full sample				
Computer usage rate	-.837	-.051	-1.033	.339
	(.133)	(.327)	(.100)	(.191)
Scientists and engineers/ total employment	.782	-3.712	-4.702	3.546
	(.573)	(1.676)	(.545)	(.949)
B. Manufacturing sample				
Computer usage rate	.421	-.731	-.899	.197
	(.300)	(.965)	(.272)	(.576)
Scientists and engineers/ total employment	2.182	-5.935	-2.992	1.214
	(.803)	(2.897)	(.850)	(1.761)
R&D/sales	3.494	-15.706	-5.808	2.440
	(1.858)	(6.432)	(1.872)	(3.666)
Computer investment/ total investment	.583	4.543	1.222	.954
	(.905)	(2.823)	(.827)	(1.700)
Total factor productivity growth rate	-2.203	14.428	3.693	2.251
	(1.804)	(5.445)	(1.530)	(3.834)

Note: Shown are the estimated coefficients for measures of technology in multinomial logit regressions, where remaining at the same job for two years is the omitted category. The regressions also include the variables listed in Appendix Table 3, 8 occupation dummy variables and a constant. The technology variables vary over time within industries. White-corrected standard errors are in parentheses. Each row is from a separate regression. Observations are weighted using the NLSY sample weights.

Appendix Table 1
Descriptive Statistics

	Job Retention		Reason for Job Separation	
	Full	Manufacturing	Full	Manufacturing
2-year retention rate	.526	.606	.555	.628
Voluntary job separation			.310	.230
Involuntary job separation			.136	.143
Age	28.0	28.0	28.0	28.0
Tenure, in years	3.4	3.9	3.4	4.0
Total work experience, in years	8.2	8.4	8.2	8.5
Highest grade completed:				
Less than high school	.10	.13	.10	.13
High school degree	.45	.54	.46	.54
Some college	.24	.16	.24	.16
College degree or higher	.21	.17	.20	.17
Enrolled in school	.11	.06	.11	.06
Married	.49	.54	.49	.54
Divorced	.11	.12	.11	.12
Female	.47	.35	.47	.34
Black	.13	.12	.12	.11
Hispanic	.06	.06	.06	.06
Unemployment rate	2.9	2.9	2.9	2.9
Number of person-years	43799	8839	41359	8500
Number of persons	8790	3283	8672	3191
Mean number of observations contributed per person	5.0	2.7	4.8	2.7

Note: Shown are weighted means for the NLSY samples used in the analysis. The weights are the sample weights in the first year for each two-year period.

Appendix Table 2
Determinants of 2-Year Job Retention Likelihood, Including Industry Computer Usage Rate

	Full Sample		Manufacturing Sample	
	Logit	R.E. Logit	Logit	R.E. Logit
Age	.023	.044	-.002	.011
	(.028)	(.043)	(.064)	(.092)
Age squared/100	-.053	-.082	-.019	-.040
	(.049)	(.075)	(.115)	(.165)
Tenure, in weeks	.379	.343	.315	.317
	(.011)	(.017)	(.022)	(.034)
Tenure squared	-.017	-.016	-.013	-.014
	(.001)	(.001)	(.002)	(.002)
Total work experience	.043	.049	.056	.056
	(.006)	(.010)	(.014)	(.021)
Less than high school	-.396	-.462	-.491	-.499
	(.056)	(.094)	(.123)	(.178)
High school degree	-.032	-.032	-.086	-.076
	(.042)	(.066)	(.101)	(.144)
Some college	-.104	-.110	-.343	-.353
	(.042)	(.067)	(.111)	(.153)
Enrolled in school	-.495	-.514	-.105	-.091
	(.044)	(.068)	(.121)	(.171)
Married	.123	.126	.217	.204
	(.030)	(.048)	(.065)	(.097)
Divorced	-.188	-.175	-.155	-.164
	(.045)	(.073)	(.096)	(.144)
Female	-.073	-.083	.058	-.048
	(.029)	(.048)	(.061)	(.091)
Black	-.022	-.032	-.116	-.116
	(.030)	(.066)	(.065)	(.130)
Hispanic	.019	.022	-.049	-.049
	(.033)	(.091)	(.070)	(.175)
Unemployment rate	.012	.015	-.006	.005
	(.013)	(.021)	(.030)	(.044)
Computer usage rate	.896	.975	.432	.419
	(.078)	(.124)	(.198)	(.295)
Log likelihood	-26225	-8764	-5276	-1788
Number of person-years	43799	43799	8839	8839
Number of persons	8790	8790	3283	3283

Note: Shown are the estimated coefficients for most of the other variables included in the regression reported in rows 1 and 3 of Table 3. Standard errors are in parentheses. The regressions also include 8 occupation dummy variables and a constant.

Appendix Table 3
Determinants of Likelihood of Involuntary or Voluntary Job Separation Instead of Job Retention, Including Industry Computer Usage Rate

	Full Sample		Manufacturing Sample	
	Involuntary	Voluntary	Involuntary	Voluntary
Age	-.086	.001	-.062	-.033
	(.041)	(.031)	(.088)	(.077)
Age squared/100	.224	-.014	.202	.031
	(.073)	(.056)	(.158)	(.138)
Tenure, in weeks	-.455	-.385	-.295	-.351
	(.017)	(.012)	(.032)	(.028)
Tenure squared	.023	.016	.013	.014
	(.001)	(.001)	(.002)	(.002)
Total work experience	-.122	-.011	-.134	-.005
	(.009)	(.001)	(.019)	(.017)
Less than high school	.748	.303	1.059	.137
	(.087)	(.063)	(.191)	(.145)
High school degree	.360	-.025	.618	-.180
	(.072)	(.046)	(.170)	(.115)
Some college	.352	.043	.640	.202
	(.072)	(.047)	(.184)	(.123)
Enrolled in school	.597	.413	-.143	.159
	(.061)	(.049)	(.183)	(.135)
Married	-.269	-.079	-.287	-.205
	(.047)	(.034)	(.093)	(.079)
Divorced	.133	.228	.019	.248
	(.068)	(.050)	(.136)	(.111)
Female	-.148	.154	-.072	.156
	(.044)	(.032)	(.087)	(.073)
Black	.194	-.094	.284	-.031
	(.043)	(.033)	(.087)	(.079)
Hispanic	.053	-.058	.050	.030
	(.047)	(.038)	(.098)	(.085)
Unemployment rate	.125	-.085	.078	-.066
	(.018)	(.015)	(.042)	(.036)
Computer usage rate	-.834	-.954	.354	-.859
	(.124)	(.088)	(.290)	(.243)
Log likelihood	-35049		-6943	
Number of person-years	41359		8500	
Number of persons	8672		3191	

Note: Shown are the estimated coefficients for most of the other variables included in the regression reported in rows 1 and 3 of Table 6. Standard errors are in parentheses. The regressions also include 8 occupation dummy variables and a constant.

Figure 1
2-Year Job Retention Rate