The impact of technology on displacement and reemployment

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Introduction and summary

The U.S. economy is booming, with 30-year lows in the unemployment rate, historical highs in labor force participation, and the lowest *displacement rates* (a measure of the incidence of involuntary job loss) in a decade. Displacement rates are especially low among groups, such as blue-collar workers, that have traditionally been most vulnerable to displacement. However, many groups may still be feeling the bite of the drawn-out corporate restructuring of the early- and mid-1990s. For example, *The Wall Street Journal* recently described the difficulty experienced by some older professional workers in finding new employment following the mass layoffs of the early 1990s (Horwitz, 1998).

Recent studies document trends in job displacement ratios and related anxiety among workers with at least five years of job tenure (Aaronson and Sullivan, 1998a, b). Like other work that analyzes job displacement, these studies focus more on the demographic determinants and consequences of displacement than on the fundamental causes of layoffs. Yet very little is known about the causes of displacement, particularly the roles of technological change, increased foreign competition, changes in domestic demand, low productivity within an otherwise growing sector of the economy, poor management, regulatory changes, or regional or national recession (Kletzer, 1998). Understanding the causes of displacement is important for policymakers charged with designing job search assistance, retraining, relocation allowances, and other programs to aid displaced workers. For example, a stronger case for training subsidies could be made for workers who are displaced due to technological reasons. Although research on the benefits of government training finds little return to such programs (relative to their cost), it is possible that the impact is more significant for workers displaced because of technology.[1] At a minimum, a relationship between displacement and technology contributes to a vast literature that shows the importance of education and training throughout a person's career.

Furthermore, the relationship between technology and displacement is important in understanding government's role in restricting natural job flows, say through the imposition of policies such as mandated severance packages in Europe intended to provide higher job security. In a technologically dynamic environment, labor markets need to be able to react to shifts in industry skill demands. While a case could be made for job security provisions if job destruction were due to poor management, unnecessarily constraining labor mobility in technologically innovative industries is likely to curtail long-run employment growth (Bentolila and Bertola, 1990).

In this article, we seek to fill a gap in the displacement literature by exploring the implications of technological change for job displacement and reemployment. We describe some reasons technological innovation might affect displacement and argue that the labor market status of less skilled and older workers might be particularly influenced by technology. We use several different datasets, including the Bureau of Labor Statistics' *Displaced Worker Survey* (DWS), to test whether high-tech sectors are more likely to displace workers and, conditional on such displacement, whether these workers find it more difficult than their peers in low-tech industries to reenter the labor market.

Our results provide evidence that industry-specific technological innovation affects the probability of displacement and reemployment. However,

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many of the results are not robust to the particular measure, or proxy, of technology used. This is not surprising since our technology proxies are from five different data sources, often do not cover the same industries, and cover a variety of topics, including computer usage, computer investment, productivity growth, and research and development (R&D) activity. Nevertheless, we find strong evidence that displacement due to the elimination of positions is more likely in high-tech industries, consistent with the notion that job destruction (and creation) is more common in technologically dynamic industries. However, there is less evidence of a correlation between technology and other forms of displacement, notably plant closings. Furthermore, we find no support for the hypothesis that the technology–displacement relationship disproportionately affects low-skilled or older workers.

Our reemployment results also vary depending on the technology proxy employed. However, our preferred variables, based on industry computer usage and R&D activity, show that increases in technology decrease the likelihood of finding new employment post-displacement. Less skilled, and to a lesser extent, older workers appear to have more difficulty finding a new job after displacement in such industries. These results point to the importance of general education and training in reducing the uncertainty associated with job loss. However, we find no evidence that industry technology matters to the probability of reemployment when other reasonable technology proxies, such as those based on productivity or computer investment, are used.

Research on displacement and reemployment

One important reason for researchers' growing interest in involuntary job loss over the past decade has been the availability of nationally representative data from the Bureau of Labor Statistics' *Displaced Worker Survey* (DWS), which began in 1984. In the DWS, a worker is considered displaced if she has an established work history (many researchers require a long history within the firm as well) and has lost her job for reasons not related to performance, such as a company layoff or plant closing. Voluntary quits, firings for poor performance, and temporary layoffs are not considered displacement. Thus far, most research has centered on two important issues: 1) Who gets displaced; and 2) What happens to these workers after displacement?

A number of studies have analyzed the size and characteristics of the displaced worker population. Recent examples are Farber (1997), Kletzer (1998), and Aaronson and Sullivan (1998a, b). These studies find that workers in blue-collar occupations, who have less education, or who work in production industries have experienced the brunt of involuntary job loss over the last 20 years. However, Aaronson and Sullivan (1998b) find that displacement has become somewhat more "democratic" during the 1990s expansion. High-seniority workers who were highly educated, were in white-collar jobs, or were employed in service-producing industries had been relatively immune to displacement prior to 1990. But during the early 1990s, displacement rates for these groups rose particularly fast, while those for some groups with high rates of displacement in the 1980s rose less or even fell.

Other studies analyze the cost of involuntary job loss by looking at the reemployment and earnings losses of displaced workers. Involuntary job loss can carry a substantial cost to workers because of the loss of job-, firm-, or industry-specific skills and experience (what economists call human capital). Workers who have been at their jobs for many years accumulate human capital that may improve their productivity and, hence, their wages. However, after a job loss, these workers may have to accept wage cuts if prospective employers do not value, and will not pay for, this job- or firm-specific human capital.[2] Likewise, workers who switch industries may suffer earnings losses due to the loss of industry-specific human capital (Fallick, 1993; Neal, 1995). Kletzer (1989), Ruhm (1991), and Jacobson, LaLonde, and Sullivan (1993) demonstrate that involuntary job loss is in fact costly, at least for workers who have attained significant tenure.[3] For example, Jacobson, LaLonde, and Sullivan found that even six years after job loss, earnings losses among a sample of Pennsylvania workers displaced in the early 1980s were equal to about 25 percent of their pre-displacement earnings levels. Recent work, including Stevens (1997) and Farber (1997), confirms these results for nationally representative samples.

Understanding the fundamental causes of displacement

While the research cited above has contributed significantly to our understanding of the impact of involuntary job loss, little work has been done on the fundamental causes of displacement. The importance of this research need is best summarized by Kletzer (1998), who notes that "one's perception of displaced workers is surely shaped by whether the underlying reason for their job loss is technological change, increasing foreign competition, changes in domestic demand, low productivity within an otherwise growing sector of the economy, poor management, regional or national recession, or some other reason."

Of the reasons mentioned by Kletzer, only the rise of foreign trade has been studied. The intuition behind the trade–displacement link is that industries facing increased import competition experience falling import prices and a decline in domestic labor's marginal revenue product. To stem the loss in domestic demand for labor resulting in a decline in productivity, wages must fall. If prices fall far enough that production becomes unprofitable, firms close plants, resulting in mass layoffs. Alternatively, wages may not fall enough because of some rigidity in the labor market, resulting in smaller-scale layoffs. Several papers, including Haveman (1994), Kletzer (1997), and Addison, Fox, and Ruhm (1995), find evidence of a correlation between import competition and domestic displacement rates, although much of this effect is driven by a few import-sensitive industries such as apparel, footwear, and textiles.

Another reason for job displacement is technological change.[4] Firms in which there are frequent changes in processes and equipment must continually retrain their employees. Training is expensive, even more so for employees who are difficult to retrain. As a result, firms in which the implementation of technology is relatively ubiquitous or which are undergoing speedy technological improvements are likely to shift their work force from those with a high cost of training to those with a low cost of training (Bartel and Sicherman, 1998). Alternatively, firms may substitute expensive-to-train employees with labor-saving machinery or equipment. This shift is likely to negatively affect certain expensive-to-train groups of workers, including low-skilled or older workers or those without previous training. Older workers may also be replaced because a firm receives smaller incremental increases in future revenues from training older employees because it has fewer years to recoup the cost of training. In addition, Kremer and Thomson (1998) suggest that high-technology firms may shift away from older workers because workers of different ages may have comparative advantages in different tasks. For example, older workers may be better managers given their extensive work experience, and younger workers might be better technicians and programmers because their recent education might allow them to adapt more readily to new equipment and technologies. Therefore, shifts toward a more technical work force (and less middle management) might result in the displacement of older workers. Similarly, a lack of training and education among less skilled workers may reduce their productivity, further reducing the demand for such workers (Baumol and Wolff, 1998).

The drop in demand for expensive-to-train workers can play out in two ways. First, firms can displace workers deemed to have high training-costs. Therefore, we look at whether the probability of involuntary job loss is higher in industries with higher levels of technology and whether older and less skilled workers are more likely to experience the brunt of this displacement activity. Second, high-technology firms can hire fewer high-training-cost workers. There is some evidence, albeit mixed, that relative utilization of skilled workers is positively correlated with capital intensity and the use of new technology.[5] That is, plants and industries that implement technology are more likely to employ skilled labor. We look at one aspect of the hiring effect by analyzing the post-reemployment patterns of displaced workers. With fewer jobs available to high-training-cost workers, reemployment is more difficult and earnings losses are exacerbated, especially among those looking for employment in high-technology industries. Therefore, not only are older and low-skilled workers more likely to be displaced than other workers in high-technology industries, they may find reemployment more difficult.

In this article, we examine only one reemployment outcome: the impact of technology on finding a new job. How long it took these workers to find a new job and at what cost, in terms of lower earnings, are left for future research.

Data and empirical strategy

Our sample consists of workers age 30 to 59 from two supplements of the *Current Population Survey* (CPS): the *Displaced Worker Survey* (DWS) and the tenure survey. The DWS is a nationally representative random survey of workers conducted in January or February of even years from 1984 to 1998. The DWS broadly defines displacement as involuntary job loss not related to worker performance. Therefore, displacement does not include quits or workers discharged for poor performance. The surveys are retrospective, asking individuals whether they have experienced job loss any time over the last five years in the 1984 to 1992 surveys and over the last three years in the 1994 to 1998 surveys. Thus, our earliest information on displacement is for 1979 and our latest is for 1997. However, we do not use the earliest DWS (1984) and CPS tenure supplement (1983) because of problems with the employment and industry codes.

For workers who report that they were displaced in the relevant period, the DWS asks for the specific reason for their displacement. The possible responses are: plant or company closed down or moved, insufficient or slack work, position or shift abolished, seasonal job completed, self-operated business failed, and some other reason. The list is less than ideal. For example, insufficient work might be the reason why one of the other events occurred. A plant may have closed because there was insufficient work to do. Position or shift abolishment is supposed to cover instances of "corporate downsizing," but it is possible that those in nine-to-five work environments will be confused by the reference to shifts. In any case, it lumps together instances of complex "reengineering" exercises, which presumably reflect long-run organizational changes, with closings of shifts in factories, which are more likely to be associated with short-run declines in demand. The seasonal job and self-employment categories do not correspond to many people's conception of job displacement and, in fact, make up only a trivial fraction of the job loss data we consider.

Finally, perhaps because of some of the ambiguities of the displacement reason categories, "some other reason" is a common response, accounting for a large fraction of the total growth of displacement of high-seniority workers during the 1990s. As it turns out, many workers reporting "other" reasons for job loss were probably not displaced. In a Bureau of Labor Statistics (BLS) debriefing of displaced workers from the February 1996 survey, only 20 percent to 30 percent of respondents who had answered "other" gave reasons that could be categorized as displacement.[6] Because it is not obvious how to construct a time-consistent displacement series using the "other" category, we focus on the first three displacement categories: plant or company closed down or moved, insufficient work, and position or shift abolished.

The first difficulty we face in constructing a consistent measure of worker displacement is that the DWS only collects information, such as the year of displacement, the worker's tenure, and other characteristics of the lost job, for one incident of displacement over the relevant period. Workers displaced twice or more in the same period are instructed to answer the additional questions for the lost job in which they had the highest tenure. This inevitably leads to some undercounting of incidents of displacement (Stevens, 1997). Moreover, as Farber (1997) notes, the change in the length of the period over which the DWS asks workers to report on displacement creates a problem of comparability over time, because the undercounting problem is more severe when the interval covered is five years long.

Our approach is to restrict our analysis to incidents of job displacement in which the affected workers had five or more years of tenure. Obviously, it is not possible to lose two such jobs in one three- or five-year interval. Thus, if workers respond accurately to the survey, the number of such job loss incidents in a year will be correctly tallied no matter whether the year is part of a three- or five-year interval in the DWS. Of course, we will miss *all* displacement incidents in which workers had less than five years of tenure. However, the consequences of job loss are not likely to be particularly great for workers who have little tenure and, thus, our measure may capture the most important forms of job displacement.[7]

To explore the impact of demographic and technological factors on displacement, we need a sample of workers who are not displaced. Because we restrict the sample of displaced workers to those with at least five years of tenure, we can only use respondents who are asked about job tenure.

We extract the job tenure data from the CPS tenure supplements conducted in January or February of 1987, 1991, 1996, and 1998.[8] With the exception of the 1994 DWS, each of the tenure supplements corresponds within one year to a DWS supplement. To account for business cycle changes in displacement rates, we do not include DWS surveys without a matching tenure supplement.

The final sample includes roughly 94,000 workers, but the regression samples vary depending on the technology proxy we use. This is because some of the technology measures cover a limited number of industries. Panel A of appendix 1 gives unweighted descriptive statistics for the sample of workers that are included in the displacement or reemployment analysis and that match to one of our technology measures, industry computer usage. Approximately 10 percent of these workers are from the DWS (and therefore are displaced). However, this is not the *annual* displacement rate; it is based on whether displacement occurred in the previous three- or five-year period. Approximately 79 percent of the displaced sample had obtained new employment by the survey date. Of those who were displaced two or more years prior to the survey date, approximately 88 percent had obtained new employment.

Technology measures

We link the DWS and the tenure supplements to a variety of proxies of industry-specific rates of technological change.[9] We use five different proxies because no single measure perfectly describes technology usage. They are:

- employee computer usage,
- investment in computer equipment,
- total factor productivity (TFP),
- output per hour (labor productivity), and
- a list of high-technology industries based on the share of R&D employees from Luker and Lyons' (1997) article in the *Monthly Labor Review* (MLR high-tech).

Below, we describe these variables in more detail. Descriptive statistics are reported in panel B of appendix 1. Other variables that have been employed in the literature, such as the National Science Foundation data on R&D spending, scientist employment, or patent data, are not used (directly) here because they are typically restricted to one or two sectors.[10] We use the R&D data indirectly through the MLR high-tech indicator.

We follow Bartel and Sicherman (1998) in exploiting only the cross-sectional nature of the technology proxies. When multiple years of data are available, as they are for many of the variables, we usually average across years.[11] This reduces the amount of measurement error in our already imperfect proxies. However, an alternative and interesting way to explore the data would be to use the time-series variation as a measure of the change in technological usage within industries.

Our first technology proxy measures the share of employees who are computer users in each industry. The data are compiled in Autor, Katz, and Krueger (1998) using the October 1993 CPS. As part of the Education Supplements, the CPS survey asked workers whether they use a computer at work, defining a computer as a desktop terminal or PC and not a handheld data device or electronic cash register. Since an affirmative response only requires use of a keyboard, it may not be a perfect measure of actual computer users; a programmer is counted the same way as a data entry operator. Furthermore, technological improvements that are not related to keyboard usage are ignored. Still, this variable is appealing because it provides data for virtually the entire economy and it attempts to measure the spread of computer technology as an explanation for skill-biased change. Many analysts argue that the computer revolution is the most viable explanation for increases in technology over this period.

Our second measure of the spread of computer technology is an industry's share of investment in computer equipment. These data are reported in the 1992 industry census reports of four major industry groups: manufacturing, retail trade, wholesale trade, and services. Like the computer usage variable, this variable attempts to proxy for the computer revolution. It has a further advantage over R&D or scientist measures in that it measures actual usage rather than potential usage. It is, however, limited in its coverage of industries.

The next two technology proxies are productivity measures. The total factor productivity (TFP) data are from the National Bureau of Economic Research's manufacturing productivity database, described in Bartelsman and Gray (1996). TFP as a proxy of technological progress has firm roots in economics, dating back to the seminal work of Robert Solow in the 1950s. TFP is the portion of output growth unexplained by labor, energy, or capital input growth. As a residual, it is an amalgamation of all of the unmeasured factors contributing to growth. Therefore, it is a rough, albeit well-utilized, measure of technological change. However, an important disadvantage of the TFP data is that they are restricted to manufacturing firms.[12] Because of concern about the volatility of the data, we use industry TFP averaged between 1980 and 1994.

Our second productivity measure is output per hour (labor productivity), as calculated by the BLS. The BLS productivity data include sectors in mining, manufacturing, transportation, trade, finance, and services, but exclude many sectors.[13] We average the productivity data between 1987 and 1996.

Finally, we use a list of high-technology industries compiled in a recent article in the *Monthly Labor Review* (MLR) (Luker and Lyons, 1997).[14] The list is based on earlier work by Hadlock, Hecker, and Gannon (1991), who used the BLS *Occupational Employment Statistics Survey* to "identify R&D-intensive industries in which the number of R&D workers was at least 50 percent higher than the average proportion of all industries surveyed." As such, this measure picks up another common indicator of industry-wide technology implementation, the use of R&D and patents.

Clearly, all of these industry measures suffer from the same aggregation problem. Although we use relatively detailed industry sectors, we cannot hope to identify the important within-industry differences in technological usage. A striking example is the computer programming, data processing, and other computer-related services industry,[15] which most would consider a high-technology industry.[16] However, this industry includes both high-tech and low-tech sectors, combining hardware and software programmers with keypunch services. Note that our measure of computer usage could conceivably count as many computer users in a data-processing firm as in a state-of-the-art computer-programming firm. As a result of the limitations of the DWS and tenure surveys, our analysis misses important subtleties about the role of technology and displacement.

A second general concern is that the technology measures may be credited with too much information about industry trends. Since we do not control for cross-sectional factors, such as trend output growth, that could be correlated with both displacement and technology usage, our estimates of the impact of technology may be biased. However, we include year indicators, allowing us to isolate the importance of economy-wide trends. Furthermore, in much of the analysis to follow, we control for the major industry (say manufacturing versus services, as opposed to computer services versus health services), allowing for fundamental industry differences to be measured.

Box 1 describes our empirical approach to testing the relationship between technology and displacement and reemployment. The basic idea is to relate demographically adjusted industry displacement and reemployment rates to industry technology characteristics. The regression results are first reported with the full sample. To test whether displacement and reemployment probabilities vary with age and skills, we also stratify the sample based on age and

BOX 1

Empirical strategy

To test the relationship between technology and displacement and reemployment, we employ a simple regression framework. In each period, a worker reports whether she has been displaced in the previous three (or five) years, and, if so, whether she has been reemployed since the displacement. The displacement analysis relates whether the individual has been displaced, as denoted by Y_{ijt}, to a group of demographic variables and industry technology measures

1) $$Y_{ijt} = \alpha + \beta X_{ijt} + \delta T_j + \varepsilon_t + \varepsilon_{ijt},$$

where i indexes individuals, j indexes industries, and t indexes time. X_{ijt} is a vector of individual demographic variables such as age, race, education, and gender. The variable T is the rate of technological implementation in industry j. Note that the subscript on T does not include t since the technology measures have no time dimension; they have been averaged across years. The ε_t term picks up the unobserved component of displacement likelihood that is due to the year of the survey. Therefore, this error term controls for business cycle effects on displacement. The ε_{ijt} term is the residual, or unexplained portion, of the equation.

Of those displaced individuals, we look at whether they are reemployed by the survey date. We ascertain reemployment using a question on how many jobs the worker has had since being displaced. If she answers one or more or reports being employed at the survey date, we code her as reemployed. To measure the impact of the industry technology variables on the likelihood of reemployment, we run an analogous regression to equation 1 but substitute the dependent variables

2) $$R_{ijt} = \alpha + \beta X_{ijt} + \delta T_j + \varphi D_{ijt} + \varepsilon_t + \varepsilon_{ijt},$$

where R_{ijt} is equal to one if the displaced worker has found new employment and zero if she remains jobless by the CPS survey date. To account for differences in the length of time since displacement, the variable D_{ijt} records the interval, in years, between displacement and the survey date.

Because the dependent variable in both equations 1 and 2 can only equal zero or one, we estimate these regressions using a *probit* framework, a technique that is commonly employed for discrete choice analysis. The probit model is based on a regression where the worker is, say, either displaced ($Y = 1$) or not displaced ($Y = 0$). This is estimated as

$$\text{Prob}[Y_i = 1] = \Phi(\beta X_i + \delta T_j).$$

From the probit results, we report partial derivatives, which give the change in the probability of an outcome (say, displacement) with respect to a change in some explanatory variable. For a given variable X, the derivative is

$$\frac{\partial E[Y]}{\partial x} = \phi(\beta X_i + \delta T_j)\beta,$$

where ϕ is the standard normal density function. In the case of the technology measures, the independent variables are measured at their mean values. However, since many of our independent variables are 0–1 dummy indicators, these derivatives are calculated as the difference between the cell probabilities when the event occurs (say, a college graduate) and when the event does not occur (not a college graduate):

$$\text{Prob}[Y = i | X',1] - \text{Prob}[Y = i | X',0],$$

where $X',1$ is the vector of covariates where the college graduate variable is set to one and $X',0$ is the vector of covariates where the college graduate variable is set to zero. All derivatives are calculated at the base case of a 30- to 34-year-old white male with a high school education in 1998.

TABLE 1

Probability of displacement, by reason

	All Displacement	Plant closing	Slack work	Position abolished
Age 35–39	–0.007*	–0.004*	–0.004*	0.001
	(0.002)	(0.002)	(0.001)	(0.001)
Age 40–44	–0.016*	–0.006*	–0.007*	–0.001
	(0.002)	(0.001)	(0.001)	(0.001)
Age 45–49	–0.014*	–0.006*	–0.006*	–0.001
	(0.002)	(0.002)	(0.001)	(0.001)
Age 50–54	–0.018*	–0.007*	–0.008*	–0.001
	(0.002)	(0.002)	(0.001)	(0.001)
Age 55–59	–0.016*	–0.006*	–0.008*	0.000
	(0.002)	(0.002)	(0.001)	(0.001)
High school dropout	0.033*	0.019*	0.011*	–0.002
	(0.003)	(0.002)	(0.001)	(0.001)
Some college	–0.006*	–0.007*	–0.002*	0.005*
	(0.002)	(0.001)	(0.001)	(0.001)
College graduate	–0.028*	–0.019*	–0.008*	0.004*
	(0.002)	(0.001)	(0.001)	(0.001)
Black	–0.004	–0.003	0.000	–0.001
	(0.003)	(0.002)	(0.001)	(0.001)
Hispanic	0.005	0.005*	0.003	–0.003*
	(0.003)	(0.002)	(0.002)	(0.002)
Other race	–0.008	–0.004	0.003	–0.004*
	(0.004)	(0.003)	(0.002)	(0.002)
Female	–0.010*	–0.002*	–0.007*	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Year 1986–88	0.085*	0.060*	0.033*	0.002*
	(0.003)	(0.003)	(0.002)	(0.001)
Year 1990–92	0.092*	0.061*	0.031*	0.007*
	(0.003)	(0.003)	(0.002)	(0.001)
Year 1996	0.032*	0.007*	0.025*	0.005*
	(0.003)	(0.002)	(0.002)	(0.001)
Log likelihood	–26,501	–16,444	–9,315	–8,672

*significant at the 5 percent level.

Notes: Partial derivatives are reported with standard errors in parentheses. See text and box 1 for an explanation. Each column represents a separate regression. Sample size is 94,155.

education groups. Therefore, in the case of skills, we estimate two separate displacement regressions, one for sample respondents who do not graduate from college and one for those who do. In the case of age, we estimate separate regressions for workers aged 30 to 39, 40 to 49, and 50 to 59.[17]

Relationship between technology and displacement

Table 1 reports our basic findings on the demographic determinants of displacement, including age, education, race, gender, and time. Each column reports results from a separate analysis. In column 1, the dependent variable is whether the individual has lost his job due to a plant closing, slack or insufficient work, or position or shift abolished. The remaining columns look at each reason separately.

The numbers (partial derivatives) in table 1 indicate the change in the probability of an outcome for each of the listed demographic control characteristics, relative to the base case (a white male, age 30 to 34, with a high school education in 1998). Since the demographic characteristics can only take on values of zero or one, we evaluate the change in each explanatory variable by "turning the variables on and off." For example, the age 35 to 39 row evaluates the change in the probability of the base case individual's chance of being displaced if all that is changed is that he is 35 to 39 instead of the base case of 30 to 34. In this case, column 1 shows that being age 35 to 39 decreases the probability of job displacement by 0.7 percentage points (with a standard error of 0.2 percentage points) relative to a 30- to 34-year-old worker.

Column 1 shows that some workers are more prone to displacement. For our purpose, two observations are worth emphasizing. First, older workers are less likely to be displaced than younger workers. Moving from the 30 to 34 age group to the 40 to 44 age group decreases the probability of involuntary job loss for high-tenure workers by roughly 1.6 percentage points. The decline becomes 1.8 percentage points by age 50 to 54. Likewise, less educated workers are more likely to be displaced. High school dropouts are 3.3 percentage points more likely to lose their job relative to high school graduates, while college graduates are 2.8 percentage points less likely to lose their job relative to high school graduates. The year indicators at the bottom of the table capture both business cycle dimensions and survey effects. Since multiple tenure and DWS surveys are coded together (that is, the 1986 to 1988 dummy includes the 1987 tenure survey and the 1986 and 1988 DWS), the derivatives should not be interpreted as pure business cycle effects.[18] See Aaronson and Sullivan (1998a, b) or Faber (1997) for analysis of displacement trends and their relationship to the business cycle.

Some interesting differences arise when we report the displacement results separately for each of the three reasons (see table 1, columns 2 to 4).

TABLE 2

Effect of technology on displacement: Probability of displacement, by reason

	Full sample		Sample size
All displacement			
Computer usage	–0.020* (0.003)	0.009 (0.006)	92,898
Computer investment	0.007 (0.008)	0.078* (0.010)	39,667
MLR high-tech	0.038* (0.002)	0.006* (0.003)	93,536
Output per hour	0.003* (0.001)	0.005* (0.001)	36,025
Total factor productivity	–0.004* (0.002)	–0.004* (0.002)	19,780
Position abolished			
Computer usage	0.012* (0.001)	0.018* (0.002)	92,898
Computer investment	0.009* (0.003)	0.017* (0.004)	39,667
MLR high-tech	0.005* (0.001)	0.003* (0.001)	93,536
Output per hour	0.0010* (0.0002)	0.0007* (0.0003)	36,025
Total factor productivity	0.002* (0.001)	0.002* (0.001)	19,780
Includes major industry controls	no	yes	

*significant at the 5 percent level.

Notes: Partial derivatives are reported with standard errors in parentheses. See text and box 1 for an explanation. Each cell represents results from a separate regression. For all displacement, dependent variable is one if individual lost job because of plant closing, slack work, or position or shift abolished, zero otherwise. See text for details. For position abolished, dependent variable is one if individual lost job because of position or shift abolished, zero otherwise. Computer usage is the fraction of workers that use a computer keyboard from the 1993 October CPS supplement. Computer investment is the share of investment in computer equipment from the 1992 Census of industries. MLR high-tech is the *Monthly Labor Review's* high-tech industries from Luker and Lyons (1997). Growth in output per hour is from the U.S. Department of Labor's Bureau of Labor Statistics, averaged over 1987 to 1996. Growth in total factor productivity is from the National Bureau of Economic Research's manufacturing productivity database, averaged over 1980 to 1994.

For one thing, older workers are relatively unlikely (but not by much) to lose a job because of a plant closing or slack work but not from a position or shift being abolished, our favored explanation of the corporate downsizing that hit many industries in the 1990s. Likewise, less educated workers are more prone to plant closings and slack work but actually less likely to be hit by a position or shift abolishment.[19] Given the demographic differences between the three job loss reasons, position abolished appears to be a different phenomenon from other reasons for involuntary job loss, hitting higher educated, white-collar workers. These results are in line with those of other researchers who have looked at the determinants of displacement using different samples of nondisplaced workers (for example, Farber, 1997).

In table 2, we add the five measures of technology to the displacement analysis reported in table 1. Each cell of the table is from a separate regression; the technology measures are added individually to the basic equation. (Because many of the technology measures are not reported for certain industries, the sample sizes vary across equations; see column 3.) The first five rows report results when the dependent variable is displacement for any of the three reasons, and the bottom five rows report results when position abolished is the dependent variable. Column 1 adds the technology measures to the exact specification used previously, and column 2 adds major industry controls to column 1.

The results using all displacement as the dependent variable vary depending on the technology proxy employed.[20] In the case of output per hour and the MLR high-tech indicator, increases in technology increase industry displacement rates. For example, row 3, column 2 of table 2 shows that being in an MLR high-tech industry increases the displacement rate by 0.6 percentage points (with a standard error of 0.3 percentage points). When industry controls are included, working in an industry with high computer investment also significantly increases the likelihood of displacement. Without industry controls, increases in computer usage and TFP actually decrease displacement. With industry controls, the impact of computer usage on displacement rates is positive, though not statistically different from zero.

The numbers at the bottom of table 2 point to a more robust result—the technology proxies are consistently correlated with a higher chance of position abolishment, regardless of whether industry controls are included. In every case, the technology effect is significant at the 5 percent level. The computer investment and usage results are particularly strong, suggesting that a 10 percent increase in industry usage or investment leads to an approximately 1.8 percentage point increase in the likelihood of having your position abolished. These results provide evidence that the elimination of positions is more likely

TABLE 3

Effect of technology on displacement, by education

	No college degree			College graduates		
			Sample size			Sample size
All displacement						
Computer usage	–0.022* (0.003)	0.000 (0.006)	65,846	–0.009 (0.007)	0.043* (0.012)	27,052
Computer investment	0.014 (0.010)	0.074* (0.012)	29,648	–0.012 (0.013)	0.061* (0.017)	10,019
MLR high-tech	0.030* (0.002)	–0.002 (0.003)	66,308	0.043* (0.004)	0.032* (0.007)	27,228
Output per hour	0.003* (0.001)	0.005* (0.001)	29,693	0.001 (0.002)	0.003 (0.002)	6,332
Total factor productivity	–0.003 (0.002)	–0.003 (0.002)	16,302	–0.008 (0.005)	–0.008 (0.005)	3,478
Position abolished						
Computer usage	0.012* (0.002)	0.017* (0.002)	65,846	0.014* (0.004)	0.029* (0.006)	27,052
Computer investment	0.013* (0.004)	0.019* (0.005)	29,648	0.003 (0.007)	0.024* (0.010)	10,019
MLR high-tech	0.004* (0.001)	0.002* (0.001)	66,308	0.011* (0.003)	0.007 (0.004)	27,228
Output per hour	0.0010* (0.0002)	0.0009* (0.0003)	29,693	0.0009 (0.0011)	–0.0002 (0.0013)	6,332
Total factor productivity	0.002* (0.001)	0.002* (0.001)	16,302	0.000 (0.004)	0.000 (0.004)	3,478
Includes major industry controls	no	yes		no	yes	

*significant at the 5 percent level.
Notes: Partial derivatives are reported with standard errors in parentheses. See text and box 1 for an explanation.
See table 2 and text for details and sources of technology measures.

in high-tech industries, but other forms of displacement, notably plant closings, are not.

Tables 3 and 4 stratify the sample to test whether low-skilled and older workers are particularly susceptible to displacement in high-tech industries. Columns 1 and 2 of table 3 report the results for a sample of workers who do not have college degrees and columns 4 and 5 show comparable results for a sample of college graduates. If less skilled workers are more likely to be displaced in high-tech industries, we would expect to see larger derivatives in column 1 than column 4 and column 2 than column 5. However, we find no evidence that such a pattern exists. In fact, the college graduate derivatives are sometimes significantly bigger than the non-college graduate derivatives.

Table 4 stratifies the sample based on the age of the worker. Again, we expect to see larger, positive derivatives for the older workers. This appears to be the case for some of the position abolished results, including computer usage and output per hour, but not for others. Therefore, we conclude that, while some evidence exists that high-tech industries are more likely to displace workers, there is no consistent evidence that this effect disproportionately affects low-skilled or older workers.[21]

We performed a number of additional tests on the results. First, we reran all of the displacement regressions using just the 1990 to 1998 surveys to see if the impact of technology has increased in the 1990s relative to the 1980s. The results are very similar and, therefore, we conclude that there is little evidence that the impact of technology on displacement has changed much between the two decades. Second, because of concern that the age 50 to 59 group may be retiring, we reran the displacement analysis for the age groups 50 to 54 and 55 to 59. The results are similar across age groups, with the strongest results coming from the computer usage and output per hour technology proxies.

In sum, we find strong evidence that the elimination of positions is more likely in high-tech industries, consistent with the notion that job losses (and gains) are more common in technologically dynamic industries. However, there is less consistent evidence of a

TABLE 4

Effect of technology on displacement, by age

	Sample: Age 30–39		Sample size	Age 40–49		Sample size	Age 50–59		Sample size
All displacement									
Computer usage	–0.023* (0.005)	0.008 (0.008)	32,791	–0.016* (0.004)	0.010 (0.008)	35,228	–0.013* (0.005)	0.003 (0.010)	24,879
Computer investment	0.013 (0.012)	0.080* (0.015)	14,515	0.013 (0.013)	0.076* (0.016)	14,773	–0.013 (0.015)	0.053* (0.019)	10,379
MLR high-tech	0.038* (0.004)	0.010* (0.005)	33,030	0.033* (0.003)	0.008 (0.005)	35,470	0.029* (0.004)	–0.007 (0.006)	25,036
Output per hour	0.003* (0.001)	0.005* (0.001)	13,374	0.002* (0.001)	0.004* (0.001)	13,173	0.002* (0.001)	0.003* (0.001)	9,478
Total factor productivity	–0.003 (0.003)	–0.003 (0.003)	7,184	–0.006 (0.003)	–0.006 (0.003)	7,157	–0.003 (0.003)	–0.003 (0.003)	5,439
Position abolished									
Computer usage	0.013* (0.002)	0.018* (0.004)	32,791	0.010* (0.002)	0.017* (0.003)	35,228	0.015* (0.004)	0.020* (0.006)	24,879
Computer investment	0.013* (0.005)	0.022* (0.006)	14,515	0.004 (0.006)	0.011 (0.007)	14,773	0.008 (0.010)	0.020 (0.012)	10,379
MLR high-tech	0.004* (0.002)	0.003 (0.002)	33,030	0.005* (0.001)	0.002 (0.002)	35,470	0.008* (0.003)	0.005 (0.003)	25,036
Output per hour	0.0008* (0.0004)	0.0004 (0.0005)	13,374	0.0008* (0.0004)	0.0006 (0.0005)	13,173	0.002* (0.001)	0.002* (0.001)	9,478
Total factor productivity	0.002* (0.001)	0.002* (0.001)	7,184	0.001 (0.002)	0.001 (0.002)	7,157	0.000 (0.003)	0.000 (0.003)	5,439
Includes major industry controls	no	yes		no	yes		no	yes	

*significant at the 5 percent level.

Notes: Partial derivatives are reported with standard errors in parentheses. See text and box 1 for an explanation. See table 2 and text for details and sources of technology measures.

correlation between technology and other forms of displacement, notably plant closings. Furthermore, we find no support for the hypothesis that the technology–displacement relationship disproportionately affects low-skilled or older workers. These results are reasonably consistent across the five technology measures.

Relationship between technology and reemployment

Next, we report results on the success of displaced workers in finding new employment. Approximately 79 percent of our displaced worker sample report finding at least one new post-displacement job by the DWS survey date. We explore whether workers who were displaced due to technology had particular difficulty reentering the labor force.

Table 5 reports the basic demographic findings from our reemployment regressions. There are several differences in these specifications relative to the displacement regressions. First, obviously the dependent variable is different. Individuals who find a job post-displacement are set to one, and everyone who is still jobless at the survey date is set to zero. Therefore, if a derivative in table 5 is positive, it implies that the characteristic is associated with a greater likelihood of finding a new job. Second, the sample includes only individuals who are displaced for one of the three reasons in the 1986 to 1998 surveys.[22] Third, recall that the displacement survey asks workers whether they were displaced in any of the past three years. Clearly, workers who have been laid off very recently are less likely to have a job as of the survey date than those displaced three years ago. Therefore, we include a series of variables to keep track of how many years ago displacement took place.[23]

The results show that older workers are more likely to be unemployed or out of the labor force following a displacement. Moving from the 35 to 39 age group to the 45 to 49 age group decreases the probability of finding a job by roughly 7.9 percentage points. The decline increases by an additional 8.2 percentage points by age 50 to 54 and a further 8.3 percentage points by age 55 to 59. Finding reemployment after a plant closing appears to be particularly difficult for older workers. Likewise, less educated workers are

TABLE 5

Probability of reemployment, by reason

	All displacement	Plant closing	Slack work	Position abolished
Age 35–39	–0.005	–0.023	0.012	0.004
	(0.016)	(0.026)	(0.030)	(0.033)
Age 40–44	–0.069*	–0.091*	–0.096*	–0.016*
	(0.017)	(0.027)	(0.034)	(0.004)
Age 45–49	–0.084*	–0.097*	–0.102*	–0.047*
	(0.018)	(0.028)	(0.035)	(0.036)
Age 50–54	–0.166*	–0.208*	–0.147*	–0.127*
	(0.019)	(0.030)	(0.037)	(0.040)
Age 55–59	–0.249*	–0.267*	–0.235*	–0.254*
	(0.021)	(0.031)	(0.041)	(0.044)
High school dropout	–0.043*	–0.069*	–0.019	0.007
	(0.014)	(0.020)	(0.027)	(0.040)
Some college	0.022	0.050*	0.015	–0.012
	(0.012)	(0.018)	(0.025)	(0.024)
College graduate	0.074*	0.088*	0.058*	0.064*
	(0.013)	(0.022)	(0.026)	(0.022)
Black	–0.094*	–0.046	–0.125*	–0.182*
	(0.018)	(0.025)	(0.036)	(0.041)
Hispanic	–0.103*	–0.095*	–0.127*	–0.092*
	(0.022)	(0.030)	(0.042)	(0.058)
Other race	–0.066*	–0.056	–0.070	–0.099
	(0.030)	(0.047)	(0.053)	(0.066)
Female	–0.031*	–0.015	–0.034	–0.070*
	(0.010)	(0.015)	(0.021)	(0.021)
1986	–0.086*	–0.023	–0.198*	–0.144*
	(0.024)	(0.034)	(0.056)	(0.051)
1988	–0.226*	–0.198*	–0.319*	–0.200*
	(0.026)	(0.037)	(0.059)	(0.057)
1990	–0.243*	–0.209*	–0.309*	–0.277*
	(0.026)	(0.038)	(0.061)	(0.052)
1992	–0.301*	–0.223*	–0.444*	–0.337*
	(0.025)	(0.037)	(0.055)	(0.048)
1994	–0.093*	–0.107*	–0.147*	–0.061
	(0.021)	(0.034)	(0.050)	(0.036)
1996	0.049*	0.070*	0.005	0.048
	(0.019)	(0.031)	(0.044)	(0.032)
Slack work	–0.072*			
	(0.012)			
Position abolished	–0.007			
	(0.013)			
1 year since displacement	0.107*	0.115*	0.124*	0.102*
	(0.012)	(0.022)	(0.024)	(0.022)
2 years since displacement	0.190*	0.210*	0.214*	0.177*
	(0.010)	(0.016)	(0.019)	(0.017)
3 years since displacement	0.207*	0.229*	0.236*	0.190*
	(0.009)	(0.015)	(0.017)	(0.018)
Log likelihood	–4,039	–1,975	–1,131	–901
Sample size	9,152	4,756	2,301	2,095

*significant at the 5 percent level.
Notes: Partial derivatives are reported with standard errors in parentheses. See text and box 1 for an explanation. See table 2 and text for details and sources of technology measures.

more likely to remain out of work. High school dropouts are 4.3 percentage points less likely to have a post-displacement job than high school graduates, while college graduates are 7.4 percentage points more likely to have a post-displacement job than high school graduates. As with older workers, those with less education have particular difficulty finding reemployment when displaced due to a plant closing.

Table 6 presents our results for the five technology measures. Like the displacement findings, the results vary depending on the technology proxy employed. In the case of computer usage and the MLR indicator, the two technology measures that encompass the entire economy, increases in technology decrease the likelihood of finding new employment when major industry trends are controlled. On average, a 10 percentage point increase in industry computer usage decreases the chances of finding a new job by 5.7 percentage points. Being in an MLR high-tech industry decreases the odds of finding a job post-displacement by 3.0 percentage points.[24] There is also a negative and large relationship between industry computer investment and reemployment but this correlation is not statistically significant. The two productivity measures exhibit no correlation with reemployment likelihood when major industry is controlled.

Table 7 reports the reemployment results stratified by education. If there is a bias towards hiring skilled workers in high-technology firms, we would expect to see larger, negative results for less skilled workers, implying that such workers are more likely to have difficulty finding a new job post-displacement. This may be because of high training costs, which could increase the likelihood that less skilled and older workers have to switch industries or take pay cuts to secure new employment. In fact, we find that less educated workers are less likely to find new employment after displacement from MLR high-tech industries and industries with higher computer usage. But we find no such relationship for the

TABLE 6

Effect of technology on reemployment

	Full sample		Sample size
All displacement			
Computer usage	–0.020 (0.021)	–0.057* (0.026)	9,069
Computer investment	0.020 (0.047)	–0.054 (0.067)	4,941
MLR high-tech	–0.038* (0.013)	–0.030* (0.014)	9,105
Output per hour	–0.008* (0.003)	–0.003 (0.004)	5,098
Total factor productivity	–0.009 (0.010)	–0.009 (0.010)	3,405
Includes major industry controls	no	yes	

*significant at the 5 percent level.

Notes: Partial derivatives are reported with standard errors in parentheses. See text and box 1 for an explanation. See table 2 and text for details and sources of technology measures.

two productivity measures or the computer investment variable.[25]

Finally, table 8 stratifies the sample based on the age of the worker. We see some evidence that older workers are more prone to employment problems when displacement occurs in high-technology industries. This result applies to the computer usage and TFP technology variables. Here, the difference in finding a new job between workers in their thirties and those in their fifties is substantial, on the order of 12 percentage points from a 10 percentage point increase in industry computer usage and 5 percentage points from a 10 percentage point increase in TFP. We do not find such an age difference for the MLR high-tech indicator.[26]

The results do not change when we restrict the sample to the 1990s surveys or to workers who were full-time when they were displaced. Tests with samples of age groups 50 to 54 and 55 to 59 are inconclusive because of small sample sizes.

In sum, our preferred measures of technology, the computer usage variable and the MLR high-tech indicator, show that increases in technology decrease the likelihood of finding new employment post-displacement. Less skilled and older workers appear to have more difficulty finding a new job after displacement in high computer usage industries. These results point to the importance of education and training in reducing the uncertainty associated with job loss.

Conclusion

This article seeks to fill a gap in the displacement literature by measuring the effect of technological change on displacement and post-displacement reemployment. Our results provide evidence that industry-specific technological innovation affects the probability of displacement and reemployment. Although the results are somewhat sensitive to the measure of technology employed, our preferred technology measures—computer usage and a measure based on

TABLE 7

Effect of technology on displacement, by education

	No college degree			College graduates		
			Sample size			Sample size
All displacement						
Computer usage	–0.023 (0.024)	–0.062* (0.029)	7,354	–0.005 (0.033)	–0.022 (0.043)	1,721
Computer investment	0.056 (0.037)	0.017 (0.081)	3,938	–0.029 (0.083)	–0.154 (0.153)	828
MLR high-tech	–0.047* (0.014)	–0.038* (0.016)	7,378	–0.013 (0.018)	–0.009 (0.022)	1,733
Output per hour	–0.011* (0.004)	–0.006 (0.004)	4,402	0.005 (0.005)	0.008 (0.006)	698
Total factor productivity	–0.009 (0.010)	–0.009 (0.010)	2,972	0.000 (0.022)	0.000 (0.022)	434
Includes major industry controls	no	yes		no	yes	

*significant at the 5 percent level.

Notes: Partial derivatives are reported with standard errors in parentheses. See text and box 1 for an explanation. See table 2 and text for details and sources of technology measures.

TABLE 8

Effect of technology on reemployment, by age

	Age 30–39			Age 40–49			Age 50–59		
			Sample size			Sample size			Sample size
All displacement									
Computer usage	0.030	–0.014	3,579	–0.031	–0.050	3,165	–0.075	–0.134*	2,325
	(0.036)	(0.046)		(0.045)	(0.055)		(0.053)	(0.062)	
Computer investment	0.030	–0.050	1,916	0.023	–0.115	1,707	0.061	0.051	1,318
	(0.073)	(0.118)		(0.105)	(0.120)		(0.107)	(0.121)	
MLR high-tech	–0.061*	–0.046	3,595	–0.029	–0.009	3,176	–0.038	–0.043	2,336
	(0.021)	(0.025)		(0.026)	(0.029)		(0.030)	(0.034)	
Output per hour	–0.008	–0.004	1,985	–0.006	–0.001	1,755	–0.016*	–0.011	1,359
	(0.006)	(0.007)		(0.007)	(0.007)		(0.007)	(0.008)	
Total factor productivity	0.011	0.011	1,296	0.012	0.012	1,150	–0.049*	–0.049*	959
	(0.018)	(0.018)		(0.020)	(0.020)		(0.020)	(0.020)	
Includes major industry controls	no	yes		no	yes		no	yes	

*significant at the 5 percent level.
Notes: Partial derivatives are reported with standard errors in parentheses. See text and box 1 for an explanation. See table 2 and text for details and sources of technology measures.

R&D employees—which cover virtually the entire economy, show consistent effects of technology on displacement and reemployment. We also explore the impact of technology on less skilled and older workers, groups that might be particularly prone to displacement due to technological innovation. While we find no evidence that the technology–displacement relationship disproportionately affects low-skilled or older workers, there is some evidence that less skilled and older workers are more likely to have difficulty finding a new job after being displaced from a high-technology industry.

We plan to conduct further research to understand why the results vary across technological measures. This includes improving our current variables by addressing measurement problems and looking at other measures that might be related to technology. In addition, we aim to study other unexplored outcomes relating to the post-displacement experience. In particular, are high-tech displaced workers more likely to face cuts in wages or hours worked after displacement? Do these workers switch industries (and face the attendant wage losses)? Are differences in the time it takes displaced workers to find new employment related to the technological level of their industry? Exploration of these issues will help us to further understand the role, if any, of technology in involuntary job loss.

APPENDIX 1: Unweighted descriptive statistics

Panel A. The sample[a]

	Unweighted means	
	Displaced workers	Not displaced workers
Age 30–35	0.194	0.156
Age 35–39	0.201	0.193
Age 40–44	0.185	0.201
Age 45–49	0.164	0.181
Age 50–54	0.137	0.151
Age 55–59	0.119	0.119
High school dropout	0.165	0.090
High school graduate	0.413	0.365
Some college	0.232	0.238
College graduate	0.190	0.301
White	0.827	0.834
Black	0.086	0.084
Hispanic	0.060	0.048
Other race	0.028	0.034
Female	0.382	0.429
Reemployed (all displaced workers)	0.785	
Reemployed (displaced 2+ years prior to DWS)	0.882	
Sample size	9,207	84,929

Panel B. Technology proxies

	Number of 3 digit industries	Mean	Standard deviation	Minimum	Maximum
Computer usage[b]	228	0.447	0.230	0.000	0.971
Computer investment[c]	119	0.108	0.120	0.002	0.682
MLR high-tech[d]	244	0.107	0.309	0	1
Output per hour[e]	110	1.700	1.932	-2.800	6.400
NBER TFP[f]	75	0.579	0.887	-2.200	3.053

[a]This is the sample from the displacement probit that uses the computer usage technology variable (table 2, row 1). Other samples vary according to industries and years used.

[b]Computer usage is the fraction of workers that use a computer keyboard and is calculated from the 1993 October CPS supplement.

[c]Computer investment is the share of investment in computer equipment and is from the 1992 *Census of Industries*.

[d]The *Monthly Labor Review's* (MLR) high-tech industries is from Luker and Lyons (1997).

[e]Growth in output per hour is from the Bureau of Labor Statistics. It is averaged over 1987 to 1996.

[f]Growth in total factor productivity (TFP) is from the NBER manufacturing productivity database. It is averaged over 1980 to 1994.

NOTES

[1]For a summary of the training literature, see LaLonde (1995).

[2]There also may be an issue of skill depreciation due to long-term unemployment. Keane and Wolpin (1997) estimate skills decline by 30 percent per year of unemployment for white-collar workers and 10 percent per year for blue-collar workers.

[3]Carrington (1993) finds that earnings losses are dependent on local, industry, and occupational labor market conditions.

[4]Many economists believe that technological change has fundamentally altered the structure of employment and wages; technology is often described as the most likely factor in the increased demand for high-skilled workers. Researchers have linked this critical change with increases in the return to a year of education and the rise of income inequality during the 1980s (Bound and Johnson, 1992; Katz and Murphy, 1992; Berman, Bound, and Griliches, 1994; Autor, Katz, and Krueger, 1998).

[5]See Bartel and Lichtenberg (1987), Berman, Bound, and Griliches (1994), and Doms, Dunne, and Troske (1997). Doms, Dunne, and Troske (1997) show a correlation between high-skill employment and technological implementation in manufacturing plants, but also show that higher tech firms employed more high-skilled workers before new technologies were introduced.

[6]Abraham (1997). For details on the debriefing, see Esposito and Fisher (1998).

[7]Farber (1997) only uses displacement that occurs in the last three years of the five-year intervals. He adjusts for differences that might still arise from workers with multiple job losses by using Panel Study of Income Dynamics data to quantify the frequency of job loss patterns and adjust rates in the DWS to offset them.

[8]We do not use the 1983 tenure supplement because it is missing industry codes.

[9]All measures are calculated at the three-digit standard industrial classification (SIC) or census industry classification (CIC) level.

[10]However, future work will incorporate these variables, as well as an aggregate index that combines all of the measures into one variable.

[11]The lone exception is the computer usage variable, which is available in 1984, 1989, and 1993. We only use the 1993 data, but, in future research, we will use the additional years as well as look at the growth in computer usage as a proxy for technological innovation.

[12]The data are reported at the four-digit level; we aggregate to the three-digit level using employment levels as weights.

[13]For example, the only three-digit sector from the finance, insurance, and real estate industry is commercial banks (SIC code 602). Only eight of 53 SIC service sectors are included.

[14]Table 1 of Luker and Lyons (1997) lists the 28 industries that are deemed high-technology.

[15]SIC code 737, CIC code 740.

[16]CIC code 740 is in the 90th percentile of the computer usage and computer investment technology measures and is coded as high-tech in the MLR high-tech indicator. It is not included in the TFP and output per hour data.

[17]An alternative method for computing age and skill variation is to interact the technology measure with the age or education variables. This method restricts all coefficients in equation 1 to be the same, whereas the stratification method allows, say, the effect of gender to vary across age or education groups. Results using interaction specifications are available upon request. We also look at age and education interactions together (that is, older, less skilled workers versus younger, less skilled workers). These results are available upon request.

[18]The 1994 displacement survey is not used because it cannot be matched to a tenure supplement.

[19]Stratifying the sample by education shows small differences in the age coefficients across education groups. The age 50–59 derivative is –0.018 (0.005) for high school dropouts, –0.015 (0.003) for high school graduates, –0.023 (0.004) for some college, and –0.022 (0.004) for college graduates.

[20]It appears that at least some of the variation is due to sample composition. For instance, restricting the sample of industries to those with TFP data (that is, manufacturing), changes the derivatives on other technology measures.

[21]In addition, we estimated the impact of technology on older, college graduates and older, non-college graduate workers. Generally, this additional interaction was not statistically significant at the 5 percent level for any of the technology measures.

[22]Unlike the displacement regressions, the 1994 survey is included in this analysis. This is because we do not have to match a tenure survey to a displacement survey in the reemployment analysis. Since no tenure survey is within a year of the 1994 displacement survey, it was dropped for the displacement analysis.

[23]The derivatives are relative to the base case of 0 years, which occurs if the year of displacement is equal to the year of the survey.

[24]Only the computer usage derivative remains significant if we look at workers displaced due to position abolishment.

[25]Only the computer usage derivative for workers without a college degree remains significant if we look at workers displaced due to position abolishment.

[26]Only the computer usage derivative for workers in their forties remains significant if we look at workers displaced due to position abolishment.

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