Chapter 9

Multitasking and the Returns to Experience

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Introduction

This chapter studies how recent changes in the organization of work, namely, the move toward multitasking, have affected the returns to work experience. In particular, I link two empirical observations about the returns to experience. First, Katz and Murphy (1992) showed that in the United States, while the returns to college have risen dramatically since the late 1970s, the returns to experience—the difference between the wages of older workers and those of younger workers at a point in time—for college graduates seemed to have been flat or even fallen. For high school graduates, the returns to experience increased from about 1976 to 1987. Autor, Katz, and Kearney (2008) update these results until 2005 and find that between 1987 and 2005, the returns to experience for college graduates did not change much, while the returns to experience for high school graduates rose through 1995 and then fell over the next 10 years. The second empirical observation that I study in this chapter is that for those entering the labor market in the late 1960s and early 1970s, wage growth over the first 10 years in the labor market was lower for college graduates than for high school graduates, while for those who entered in the late 1980s, wage growth increased over the first 10 years for college graduates so that it was almost as high as that of high school graduates (Aaronson 2001).

I analyze whether changes in the nature of jobs may be responsible for these patterns in the returns to experience. One notable change in the workplace—possibly facilitated by the advance of information technology—is the reorganization of work toward more multitasking and less specialization. A move toward more multitasking in the workplace implies that each year of experience in a job is equivalent to less time spent working on each distinct task. If wages increase with experience on the job because workers are learning how to do each task better, then the returns to an additional year on the job equal the return to experience in each task added up over all the tasks performed. If the number of tasks is sufficiently large or the return to experience in each task sufficiently large, we may observe wages over an individual's lifetime or tenure in a job going up faster than with less multitasking. We may also observe lower starting wages when there is more multitasking (as has been observed by Aaronson and others). However, this may not translate into a change in the cross-sectional returns to experience right away, consistent with Katz and Murphy's observation above. In a situation with changes over time in the level of multitasking in the workplace, the returns to experience in a cross-section may not be a good proxy for how much today's young workers will earn when they are older.

In the next section, I review the literature on the returns to experience, why they might differ according to industry or type of job, and how technical change might affect them. After this I describe the spread of new work practices including multitasking. In "Data" section, I describe the data on multitasking, including a discussion on the proxies used for multitasking and the methods used to construct a measure of multitasking for each worker in the wage data set that I exploit. Section five presents the main results and some robustness checks and the last section concludes.

Related Literature

While there has been a significant amount of research on the effect of technical change on the level of wages and on the returns to schooling, there is little work done on how technical change affects the returns to experience. Since most of literature argues that new technology is complementary to educated labor—this is the reason why educated workers gain more, relative to less-educated workers, when there is technical change—there is little scope for extending this theory to explain any changes in the returns to experience. In fact, intuitively, it appears clear that new technology should be complementary to young (and more flexible) workers rather than to older workers. My argument in this chapter is that technical change has affected the organization of work, which in turn has affected wage growth over a worker's lifetime.

There is some literature that explains why the returns to experience might be different in different jobs. In Helwege (1992), the job specificity of human capital makes older workers immobile, thereby not allowing arbitrage in their wages even though younger workers are perfectly mobile. So as long as old and young workers are not perfect substitutes, sectors experiencing a -positive demand shock will have a steeper wage-experience profile as young workers' wages are held down by arbitrage while older workers' wages remain high as their human capital is job-specific and therefore reduces mobility. Bronars and Famulari (1997) find significant differences in wage growth rates across employers and show that jobs at high-wage-growth employers tend to last longer. Finally, Neal (1998) constructs a model in which the most-able workers choose jobs with the largest job-specific component of training. Since these jobs have more training, they may also have smaller starting wages. Therefore, tenure and wage growth are both greater in these jobs.

In addition to the above, there is some literature on job-specific experience that shows why the returns to experience or tenure may increase with faster technical change. For example, Violante (2002) uses the idea of a strictly concave learning curve to show that technological acceleration leads to larger returns to tenure, since workers lose more job-specific experience when they change jobs in response to technical change. Helpman and Rangel (1999) construct a similar model in which experience is vintage-specific, so that switching vintages lowers the amount of experience and therefore raises the returns to experience. Lindbeck and Snower (2000) is one of the few papers that addresses the reorganization of work explicitly. They derive conditions under which a firm will switch from a Tayloristic mode[1] of production to multitasking. This happens if tasks become more complementary in production, if there are more learning spillovers between tasks, or if workers have more flexible human capital. However, these authors do not directly address effects on the returns to experience.

Most of the literature on multitasking, and the reorganization of work in general, studies its causes, the importance of classic economic problems such as free riding under the new form of work organization, and the increase in total output due to the introduction of new work practices. This chapter contributes to this literature by analyzing how productivity changes over a worker's lifetime under new work practices. This chapter also contributes to the vast literature on technical change and wage inequality by showing how technical change can increase the returns to experience by increasing the optimal number of tasks for a worker.

The fact that less repetition in a task may lead to faster learning on the job as a whole means that the use of new work practices should change the way wages differ across workers with different levels of experience. The effect of new technology on the role of experience as a skill is often ignored, largely because there appears to have been little change in the cross-sectional returns to experience among college graduates. Yet if technical change facilitates multitasking, then it can lead to major changes in the returns to experience by cohort as workers choose jobs according to the technology available when they enter the labor market. These changes may not be picked up if we focus only on the cross-section. If starting wages in later cohorts are lower (and wage growth higher), then the cross-sectional returns to experience will look a bit higher but not as much as those returns estimated within cohort. If the starting wages in later cohorts are higher in addition to the wage growth, then it may look like the cross-sectional returns to experience are actually going down over time. As described in introduction, it seems that the cross-sectional returns to experience have increased for high school graduates but not for college graduates. This is consistent with the mechanism described above, if college graduates have both higher starting wages and higher wage growth in later cohorts, while high school graduates have lower starting wages and higher wage growth in later cohorts. This broad story is also consistent with Aaronson's (2001) findings, and with the evidence in the next section about how multitasking has affected both blue-collar and white-collar workers but in slightly different ways.

The Increasing Importance of Multitasking

Empirical evidence suggests that this kind of a change in the organization of jobs—a move toward more multitasking—is becoming more and more common. Case studies provide most of the evidence on the movement away from specialization. In this section, I summarize studies of several different industries and provide some statistics on the extent to which these new work practices have diffused throughout the economy.

Case Studies

Manufacturing

Studies on the automobile industry are especially interesting since this sector was the basis for the model of assembly-line manufacture as exemplified in Henry Ford's factories, the standard post–Industrial Revolution structure of specialization. Yet several firm-level studies of modern times show significant movement away from this kind of organization toward a less specialized, more multitasking-oriented production model. Rinehart, Huxley, and Robertson (1997) describe the organization of work at CAMI Automotive, a joint venture between General Motors and Suzuki, in Ontario, Canada. Even in departments like materials handling, welding, and engine subassembly, each person rotates through a series of tasks. A typical worker handles equipment of varying degrees of complexity and even cleans up and performs some basic maintenance. NUMMI, a Toyota–General Motors joint venture, also made extensive use of teams. Even though the teams were eventually linked in series as in a standard mass production setup, there was job rotation, quality assurance, and preventive maintenance within each team.

Other studies of work organization in manufacturing industries include Cappelli (1999) who describes a General Electric engine plant in Massachusetts where employment fell by 50 percent in the early 1980s, accompanied by movement toward a flatter hierarchy and increased use of teams. This observation would be consistent with unproductive workers being laid off concurrently with an increase in teams, leading to higher total productivity arising from the use of teams—something to bear in mind for later empirical analysis. A similar picture emerges from Carmichael and Macleod's (1993) description of Ichniowski's case study of North American Paper Company where the advent of teams reduced the number of job classifications from 94 to

4, and led to greater job rotation. There are many other examples of new work practices in manufacturing, including Appleyard and Brown's (2001) study of the semiconductor industry; Kleiner, Leonard, and Pilarski's (2002) study of commercial aircraft manufacturing; and Bailey, Berg, and Sandy's (2001) study of the steel, apparel, and medical electronics and imaging industries.

Services

Studies of work reorganization in services are harder to come by. Autor, Levy, and Murnane (2002 present an interesting case where the introduction of a new technology led to multitasking in one department of a bank and greater division of labor in the other. The crucial difference between the two departments was that the former dealt with work that was more discretionary than the latter. That is, greater skill was required to handle the work in the former department—it was here that the new user-friendly technology led to multitasking. This may also be the kind of mechanism behind Baker and Hubbard's (2003) findings in the truck industry. They found that the introduction of some onboard computers lowered the costs associated with complex job design and therefore led to greater multitasking, while other onboard computers that provided location information and real-time communication actually led to more specialization. Citibank's organization of work units around particular markets is another example (Appelbaum and Batt 1994). In this model, each manager controls an entire transaction for a particular group of customers and the jobs of frontline workers were expanded to allow them to handle all the steps necessary for a customer request. The change from mainframes to minicomputers facilitated this change in job design. Appelbaum and Batt also describe the spread of teams and job rotation in a large telecommunications company, in the Shenandoah Life Insurance Corporation, and even in

Federal Express, where couriers planned their own routes and acted as assistant sales representatives by using their interaction with customers to inform them about new products and services.

Highly Skilled Jobs

There is a small but growing literature on specialization in highly skilled professions like law and academics. For example, Garicano and Hubbard (2002) show that the share of lawyers who specialize in one of the fields they study is higher in larger counties, in counties with state capitals, and in counties that have larger average establishment size in construction, manufacturing, transportation, utilities, or financial services. Moreover, lawyers tend to be less specialized in counties where the share of employment in manufacturing and wholesale trade is low. Garicano and Hubbard's main interest is in analyzing the conditions under which the division of labor among lawyers is better mediated by firms, rather than by the market, and their analysis is entirely cross-sectional so that there is no evidence about trends in specialization. Kendall (2002) finds that PhD graduates from better-ranked departments tend to do less-specialized research than PhD graduates employed in the same department but who graduated from lower-ranked departments, showing that higher-ability workers may specialize less.

Workers in highly skilled jobs typically have highly specialized education. So multitasking across subdisciplines within economics, for example, is probably more difficult, or requires more retraining, than multitasking across machines on the shop floor.. Suppose that the academia sector produces "knowledge", and that knowledge can be produced using two inputs, teaching and research. Each of these inputs is composed of several tasks. In particular, research comprises publications in different fields of economics, which may be considered substitutes.

For example, it might be reasonable to assume that publishing a paper in labor economics is a good substitute for publishing one in public economics while teaching is a poor substitute for research. As in Lindbeck and Snower's model and in the empirical evidence from Kendall, when the tasks involved are substitutes, multitasking may lead to each worker performing more tasks but this does not happen if the tasks are complementary.

The Diffusion of New Work Practices

What is the magnitude of this reorganization of work in the US economy? Using the survey data I turn to later in this chapter, Osterman (1994) finds that over half of all private establishments in the United States with 50 or more employees used teams and job rotation in 1992. He also finds that the higher is the skill level required in an establishment, the more likely it is that flexible work practices like teams will be adopted.[2] Ichniowski, Shaw, and Prennushi (1997) surveyed 36 US steel finishing lines owned by 17 different steel companies and found that in nearly a quarter of the cases, a majority of operators were involved in formal or informal teams, 13 percent participated in more than one team and just under 10 percent were involved in job or task rotation. Ben-Ner and colleagues (2001) studied a sample of 800 firms in Minnesota and showed that in over 40 percent of these firms, workers participated inindividual-based decision making and in a similar proportion of firms, workers participated in group-based decision making such as teams and quality circles. In a survey of approximately 300 large US firms carried out in the mid-1990s, Bresnahan, Brynjolfsson, and Hitt (2002) find significant use of teams and also find that the new work practices are complementary to the use of information technology in production. Finally, more than 60 percent of all managers in Britain around the turn of the century said that organizational change affecting nonmanual jobs had widened the range of tasks performed while for manual jobs the relevant figure was about 40 percent (Caroli and van Reenen 2001).

Data

New Work Practices and Multitasking

In this section, I describe the multitasking data used in the analysis for this chapter. I use a unique data set that comes from a 1992 survey[3] by Paul Osterman. In this survey, Osterman asked the management personnel from a random sample of American establishments about work practices and other characteristics of their establishments. An establishment is defined as a business address and is distinct from a company. In each establishment, the "most senior person . . . in charge of production of goods and services" (Osterman 1994) was asked about the extent to which various work practices had been adopted in that establishment. The advantage of surveying with a local respondent and at the establishment level is that the reported characteristics of work organization and other features of the workplace are more likely to be accurate than if one were to survey a single respondent in a large firm with multiple locations. The response rate of the Osterman survey was 65 percent.

The final sample used in this chapter consists of 806 establishments, each of which had 50 or more employees and operated in nonagricultural industries. The occupation group that Osterman focused on was that of "core" jobs in an establishment. A core job is defined as "the largest group of non-supervisory, non-managerial workers at this location who are directly involved in making the product or in providing the service at this location." The survey questions are focused on whether these core workers use various new work practices. The five main work practices considered are self-directed teams, job rotation, employee problem-solving groups

(PSG), statistical process control (SPC), and total quality management (TQM). Interviewees were asked whether each of these practices was used at their establishments, and if so, what percentage of core employees were involved. They were also asked whether employees participated in any cross-training, that is, training on various machines or various parts involved in a job. I use each of the work practices enumerated above variously as proxies for multitasking, look at the effect of cross-training, and examine the effects of including only teams, job rotation, and cross-training in a proxy for multitasking.

How well do these work practices proxy for the kind of multitasking I have described in the introduction? Hamilton, Nickerson, and Owan (2002) describe the transition of a garment facility run by the Koret Corporation from a traditional Taylorist production setup to a team or module-based production setup. In the traditional system, the sewing operation was broken into 10–30 distinct and separate operations, sewing stations were arranged in a grid on the shop floor, and each station was assigned one operation. Under the module system, each team is made up of approximately 6 or 7 members who work on sewing machines set up in a U-shaped work space. Each team member works standing up and the sewing machines are set on wheels so that identifying bottlenecks or changes in worker productivity and rearranging the workers or the machines is easy. Also, the workers are cross-trained on all the machines. In the survey, the workers claimed that they learned all the production tasks, had more information about the production tasks compared to the Taylorist system, and were able to “shift and share” tasks. So, a month of experience under the Taylorist system amounts to a month of experience on one kind of sewing machine, while a month under the module system amounts to less than a month’s experience on each of several types of sewing machines. Various studies of automobile factories also characterize teams in a similar way. Teams may eventually be placed along an assembly line but what is essential for the multitasking theory presented here is that workers acquire experience on more tasks or machines per unit time than they did under the traditional assembly-line setup. For example, in Hamilton and colleagues' description, a strip of the assembly line has essentially been shaped into a U-shape, so that instead of being exposed only to his or her own task on the assembly line, each worker is now being exposed to all the tasks along the strip. While teams do not necessarily imply multitasking in theory, the empirical studies show that the diffusion of teams is a reasonably good proxy for the movement away from specialization and toward multitasking. Of course, there may be division of labor within a team but as long as each worker has exposure to a greater number of tasks than on the assembly line, we can consider the use of teams to be a proxy for multitasking.

It is probably less controversial to interpret job rotation as multitasking. It is not immediately clear how SPC and TQM would be related to multitasking but since many of these work practices are used together, I include these as well in some specifications. I also include cross-training in many of the specifications below, since it is clear that cross-training is complementary to many of the new work practices and it is possible that the reason we observe higher returns to experience in sectors with greater use of these work practices is the higher level of training.

Table 9.1 shows the diffusion of these new work practices in the economy, and in the manufacturing sector in particular. The first two columns show the percentage of establishments in which there was some use of the work practice in question (the extensive margin), while the last two columns show the percentage of establishments in which at least 50 percent of the employees in core jobs were involved in the work practice in question (the intensive margin). Nearly 80 percent of all establishments were involved in one or more of these new work practices, and this proportion rises to nearly 85 percent for manufacturing establishments. Among these, 50 percent of manufacturing establishments were involved in teams, as were nearly 55 percent of all establishments. Job rotation appears to be the most common new work practice in manufacturing (nearly 56%), though the difference in the use of various practices is not very large.

TABLE 9.1 HERE

The third and fourth columns show that at a significant proportion of these establishments, half or more of their core employees participate in these new work practices. At this intensive margin as well, job rotation seems to be the work practice that is most popular in manufacturing, with more than 37 percent of manufacturing establishments having at least 50 percent of their core employees involved in job rotation.

There is considerable anecdotal evidence that the new work practices studied by Osterman are complementary and, in particular, that establishments which use these teams or quality circles intensively also tend to use more cross-training. As table 9.2 shows, at the intensive margin, establishments that use teams do tend to use job rotation and cross-training as well. So, any finding that jobs with a higher use of teams also have higher returns to experience may be explained by workers in these jobs acquiring more training, and in particular, training in multiple tasks. The respondents in Osterman's survey were also asked whether the skills involved in the core job in their establishment have become more complex in the last few years. The last row of table 9.2 shows that the core job in establishments that use more teams is reported to have become more complex, though this effect is very small. The same is not true for job rotation. The first observation may justify the interpretation of teams as multitasking, though these effects are small. The second observation may indicate that the appropriateness of interpretation of teams and job rotation as multitasking differs according to the kind of job, as explained next.

TABLE 9.2 HERE

One final source of ambiguity concerning the interpretation of these work practices as evidence of multitasking involves the distinction between job rotation and the use of teams. In particular, since tasks are often shared by or rotated within teams, some respondents may use these terms interchangeably. In addition, a work practice drawing on the use of both teams and job rotation may be labeled as “teams” in better or higher-status jobs, and “job rotation” in worse or lower-status jobs. Osterman finds that the percentage of manufacturing establishments with blue-collar core workers—those with arguably lower-status jobs—that use only teams is almost equal to the percentage that use both teams and job rotation. More than 14 percent of nonmanufacturing establishments whose core workers are not blue collar use only teams while less than 6 percent of blue-collar manufacturing establishments use only teams. Similarly, only 7 percent of the former use only job rotation compared to nearly 12 percent of the latter.

These figures imply two important things for the empirical analysis. First, the term “teams” may be acting as a proxy for “good” jobs and conversely, the term “job rotation” may be acting as a proxy for “bad” jobs. In addition, using either teams or job rotation may better signal multitasking than using any single distinct work practice.

Wages and Individual Characteristics

The main problem with using these data on new work practices to test the effects of multitasking on wages is that the Osterman data set does not include data on wages or individual characteristics.[4] To obtain this information, I use annual data from the Panel Study of Income Dynamics (PSID). This data set contains demographic and other information on about 6,000 families and 15,000 individuals interviewed every year since 1968. Due to problems with data quality and missing variables, I only consider observations from 1970 to 1992. The data set used in the following regressions consists of information on white males with up to 40 years of experience, who are heads of household, and who are either working, temporarily laid off, or looking for work. Following the literature, only those who worked for 1,500 hours or more during the survey year—that is, full-time, full-year workers—are included in the wage regressions. The wage measure used is the logarithm of hourly real wages, where wages are deflated by the CPI (1982–1984 = 100). Hourly wages are constructed by dividing annual wages by hours of work in the survey year. Since there are significant discrepancies in the data, I clean two of the most important variables, years of schooling and age, following the procedure outlined in Lillard (2001). Because the multitasking data refers only to those in core jobs—that is, only nonmanagerial, nonsupervisory workers—I use only these classes of workers for the regressions in which I test the connection between multitasking and wages. These regressions also include time dummies in order to control for economy-wide wage trends or disturbances.

Empirical Strategy

I start by investigating whether the second stylized fact referred to in the introduction, namely, successive cohorts have different returns to experience over their lifetimes, is in fact evident in the PSID. Then I check to see whether there is any systematic change in the type of sector in which successive cohorts are choosing first jobs. Next, since the PSID is a panel, I am able to explore the correlation of wage growth within a job (for those who did not change jobs in the data set) with job-level measures of multitasking matched from the Osterman data. This gives us some idea about the differences across jobs in wage growth and the extent to which these differences are related to the level of multitasking in a job. I then ask directly whether multitasking is associated with higher returns to experience by estimating the returns to experience by industry (or industry-occupation) and examining the correlation of these estimated returns with the level of multitasking in that industry (or industry-occupation). I also estimate a wage regression that includes the level of multitasking interacted with the level of work experience. Finally, I discuss the implications of unobserved individual heterogeneity.

Estimating the Returns to Experience by Cohort

How do the returns to experience vary by cohort in the data? I first estimate the following wage regression for all the workers, indexed by *i*, in the PSID sample described in "Wages and Individual Characteristics" subsection—not just those in core jobs—to check whether these data exhibit cohort effects in the returns to experience that are similar to Aaronson's (2001) results. The wage specification is as follows:

$$\begin{aligned} lnw_{it} = {} & b_0 + b_{11}School_i + b_{12}School_i^2 + b_{21}Exper_i + b_{22}Exper_i^2 + b_3Cohort_i \\ & + b_{41}School_i * Cohort_i + b_{42}School_i^2 * Cohort_i + b_{51}Exper_i * Cohort_i \\ & + b_{52}Exper_i^2 * Cohort_i + b_6Dem_{it} + e_{it} \end{aligned} \tag{9.1}$$

where w is the hourly real wage as noted in the Wages and Individual Characteristics sub-section; *School* is the years of schooling completed, *Exper* is constructed as *Exper* = *Age*-6-*School*, where *Age* is the age in years; *Dem* is a vector of demographic characteristics including dummies for sex, race, state, union membership, industry and occupation; and *Cohort* is defined the period in which the worker entered the labour market (constructed using information about age and years of schooling).

The data are divided into 14 cohorts. Dropping the 2 oldest cohorts plus the youngest cohort, to ensure there are adequate observations in each cohort, leaves 11 cohorts of workers in the final analysis data set, as indicated in table 9.3. Naturally, it will be necessary to disentangle the cohort and potential experience effects in the above regression. As shown in table 9.3, the grouping of workers falling into a range of entry years into the same cohort produces some variation in experience within each cohort at a point in time. Notably, observations on experience are drawn from the wide range of 0–14 years for cohorts 8, 9, and 10. Thus, I can estimate the level of wage growth between years 0 and 14 for each of these cohorts and compare these estimates to explore whether there is any cohort difference in the returns to experience.

TABLE 9.3 HERE

Table 9.4 reports the results from estimating the wage regression shown above. The coefficients reported are the estimated returns to experience, by schooling group and cohort. Workers with a higher level of schooling have higher returns to experience, irrespective of cohort, though these differences are often insignificant. More importantly, starting from the cohort entering the labor market between 1973 and 1977, later cohorts have higher returns to experience. Since I have controlled for the level of education, this cohort effect is not due to changes in composition (later cohorts have a higher average level of education). This means that higher returns to experience could be observed if there has been a change in the quality of education, a change in actual work experience (given potential experience), or a change in the price of either of these inputs, for later cohorts.

TABLE 9.4 HERE

Now that we have seen some evidence that later cohorts do indeed have higher returns to experience, the next item on the agenda is to see whether this may be explained by multitasking. That is, do later cohorts choose jobs with a greater number of tasks, and does this job choice lead to higher wage growth? We only have multitasking data for nonsupervisory, nonmanagerial workers, so we will only be able to address this question for these workers (of whom some are nonmanagerial professionals).

Unfortunately, we do not have observations on work reorganization at the level of disaggregation of the individual or the job. Instead, on the one hand, we have wage and individual characteristics for each worker and, on the other hand, measures of multitasking at the establishment level. Because the workers in the PSID are not matched to the establishments in the Osterman data, some algorithm must be used other than a simple merge by establishment in order to connect a worker with a measure of multitasking. My solution is to aggregate the multitasking measures from the establishment level up to the 3-digit SIC industry level and then assign each worker a level of multitasking according to his or her current industry, or current industry-occupation pair.

The two measures of multitasking I focus on are (1) the percentage of establishments in each 3-digit SIC industry in which at least 50 percent of the core employees were involved in the work practice (which I call industry-level multitasking) and (2) the percentage of establishments in each industry in which at least 50 percent of the employees in a particular 1-digit Standard Occupational Classification (SOC) occupation are involved in each work practice (which I call job-level multitasking). So, for a particular worker, the first measure captures the percentage of establishments in his or her industry that use multitasking but not necessarily whether that use applies to workers in his or her occupation. The second measure is narrower, focusing on what percentage of establishments in the worker's industry has core jobs in his or her particular occupation that use multitasking. In other words, the first measure relates to the probability that multitasking is occurring somewhere in the worker's industry while the second relates to the probability that it is occurring in his or her occupation.

Not all SOC occupations are represented in the core jobs included in the work practices data, which means than we can use the second measure described above only for a smaller number of workers. Also, the multitasking measures are only available for 1992. Yet, the multitasking literature documents significant differences across sectors—not only across time—in the degree of work reorganization. Using these data we can determine whether there are inter-sectoral differences in the returns to job tenure and experience, and how these differences relate to inter-sectoral differences in the level of multitasking.

Cohort Effects in Choice of Sector

Before we try to relate the level of multitasking directly to wage growth in a sector, it is useful to look at whether there are systematic differences in the kinds of sectors successive cohorts of workers choose for their first jobs. If multitasking leads to higher job tenure (e.g., because of greater training), then the first job may play a more important role in determining the career trajectory of later cohorts of workers.

As noted earlier, we only have work practices data for 1992, so we cannot observe differences in the level of multitasking across the jobs chosen by labor market entrants of different cohorts as measured in the years those jobs were chosen. Instead, using only the 3 cohorts for whom we have wage observations from 1992, we can explore whether there are systematic differences in these workers' choice of sector across different levels of multitasking as observed in 1992.

To perform this analysis, I first assigned each individual an industry-wide level of multitasking based on the sector in which s/he had his/her first job rather than his/her current job. Then, to produce cohort-specific results for tabulation, I averaged the industry-level measure of multitasking assigned to each worker over all individuals in that cohort.

Tables 9.5 and 9.6 show the results of this exercise for high school and college graduates, respectively. For the 1973–1977 cohort, table 9.6 shows that the typical sector chosen for a first job by a college graduate saw nearly 48 percent of establishments involved in teams in 1992. Note that this cohort had nearly 20 years of experience in 1992. In contrast, the typical sector chosen by the 1983–1987 cohort had nearly 54 percent of establishments involved in teams in 1992. According to this, college graduates in the later cohorts were entering sectors that subsequently, in 1992, had a larger percentage of establishments using teams. A college graduate entering the labor market in 1983–1987 was more likely than a college graduate in an earlier cohort to start off his/her career in a sector that would go on to use teams in 1992. As shown in table 9.5, this is clearly not true for high school graduates. It is also apparent in table 9.6 that the sectors where college graduates in the 1973–1977 cohort have their first jobs are quite unlikely to have job rotation and this small number falls for later cohorts. By contrast, the analogous figure for high school graduates, in table 9.5, is much larger and rises in successive cohorts. This pattern may be another indication that job rotation is a proxy for a “bad” job.

TABLE 9.5 HERE

TABLE 9.6 HERE

It is safe to assume that when the 1973–1977 college graduate cohort entered the market, there was little use of teams anywhere. So if we found thatfor this cohort wage growth in the first 10 years was higher for those who chose sectors that went on to have greater multitasking in 1992, this may be because of some characteristic of the sector related to its being more likely to have, in 1992, both teams and steeper wage profiles. The possibility of such third-party factors means that these results do not necessarily imply a causal relation between the level of multitasking and wage growth.

Multitasking and Wage Growth within a Job

One way to see whether multitasking is associated with higher wage growth is to compute the increase in wages within a job over time and relate that increase to the job-level measure of multitasking. However, before undertaking this exercise, it is instructive to see how the use of multitasking relates to the average characteristics of workers in a sector. Table 9.7 shows the correlation between use of the various work practices at the industry-occupation level as measured in 1992 and industry-occupation-specific average individual characteristics calculated from the PSID data. Since the multitasking data are from 1992, to generate average individual characteristics I compute the average schooling level and experience level by industry-occupation group in 1990–1992 from the PSID, pooling these 3 years in order to increase the number of observations. The first two columns of this table show the effect of schooling and experience, respectively, while the last two columns show the effect of experience within each schooling level. Table 9.7 shows that sectors in which workers have a higher average level of education not only tend to have more extensive use of teams but also feature lower use of job rotation. This again is consistent with the interpretation that job rotation acts as a proxy for bad jobs. More importantly, sectors with younger workers tend to use more of all the listed work practices. Since in this table we are looking at correlations at one point in time, the younger workers are those belonging to later cohorts. This pattern then implies that there is greater use of teams and job rotation among later cohorts.

TABLE 9.7 HERE

Next, I test whether wages rise faster in jobs with greater multitasking. Since the PSID is a panel, I can track individuals' wages over time but due to observing multitasking proxies in only 1992, I only look at those who have not changed jobs in the period 1983–1992 and compute the average annual growth in hourly wages over this period. I assume that the level of multitasking in 1983 is 0, which is fairly consistent with anecdotal evidence on the rise of new work practices. The level of multitasking in 1992 then also represents the change in the degree of multitasking in the preceding 10 years.

Table 9.8 presents results on the relationship between multitasking measures at the industry-occupation level and the within-job wage growth among workers in the PSID who did not change jobs from 1983 to 1992.

TABLE 9.8 HERE

The main observation from table 9.8 is that jobs featuring a greater use of teams have higher within-job wage growth both overall and within schooling and experience groups. The correlation between multitasking and wage growth is smallest among young high school graduates but as high as 8 percent among young college graduates. Surprisingly enough, the correlation is higher for older high school graduates than for younger ones. This may be because more-skilled workers within a group are more likely to work in teams whereas less-skilled ones are more likely to engage in job rotation. The second row of table 9.8 shows that, consistent with this story, job rotation is associated more with the wage growth of young high school graduates than with the wage growth of any other group. Also, cross-training is associated with increases in wage growth for young high school graduates but with decreases in wage growth for older high school graduates and all college graduates. These two results again imply that job rotation and cross-training may act as proxy for relatively bad jobs—higher-status workers do not rotate between jobs or train on multiple machines, or if they do these sorts of activities, it is not labeled "job rotation" or "cross-training"—which may bias the estimated coefficients of the wage regression. Finally, both SPC and TQM seem to have a positive effect on the wage growth of young college workers while participation in PSG lowers the wage growth of older high school graduates and to a smaller extent, young college workers. It is important to remember that these results hold only for those who have been in the same job from 1983 to 1992 and so should not be extrapolated to job changers. In "A Final Look at the Effects of Unobserved Individual Heterogeneity" subsection, I present some results on those who change industry-occupation combinations over this period to explore the effects of unobserved individual heterogeneity.

The Returns to Experience and Multitasking

The results presented so far indicate that there is a correlation between the level of multitasking in a sector and the level and growth in wages in that sector. One concern with the results discussed in "Multitasking and Wage Growth within a Job" subsection is that wage growth might be larger for those who remained within a job for 10 years because of some other individual characteristic, which also implies longer job tenure and the choice of a sector with more multitasking. In order to get a clearer picture about whether this is true, I first estimate a standard Mincerian wage regression to find the job- and industry-level returns to experience. The estimated equation is as follows:

$$lnw_{it} = b_0 + b_{11}School_i + b_{12}School_i^2 + b_{21}Exper_i + b_{22}Exper_i^2 + b_3D_{it} + b_{41}School_i * D_{it} + b_{42}School_i^2 * D_{it} + b_{51}Exper_i * D_{it} + b_{52}Exper_i^2 * D_{it} + b_6Dem_{it} + e_{it} \quad (9.2)$$

In equation 9.2, D_{it} is a vector of dummy variables indicating the industry (or industry-occupation) in which individual i works at time t (the excluded industry-occupation pair is construction-production). I relate these estimates with the sector level of multitasking to see whether the returns to experience are indeed higher in sectors with more multitasking. Again, because the multitasking measures are only available for 1992, the wage and other individual data are taken from the PSID data from 1983 to 1992. As before, I include the economy-wide unemployment level for each year. At the industry-occupation level, I pool the wage and individual data from 1983–1992 to ensure adequate observations because, as explained in "Estimating the Returns to Experience by Cohort" subsection, not all occupations are represented in the core jobs, so the number of observations with a common industry-occupation combination is much smaller than the number with a common industry.

Industry and industry-occupation specific returns to experience can be generated by many phenomena, including not only differences across industries and jobs in multitasking but also factors associated with other theories that aim to explain interindustry differences in the returns to experience. According to Helwege (1992), returns to experience will be higher in sectors that face a positive demand shock. Neal (1998) implies that sectors with higher returns to experience should also have higher average levels of tenure. In order to accommodate these theories, I also include sector-level unemployment (a proxy for demand) and the average level of tenure with the sector.

In table 9.9, I show the relationship between the industry-specific and "job," or industry-occupation, specific returns to experience and the level of multitasking in that industry or job in 1992. The first column in table 9.9 presents the correlations between the industry-specific experience premia and the work practice and other industry-level variables while the second column shows the analogous correlations using the job-specific experience premium. The industry-level experience premium is higher where there is more unemployment, which contradicts Helwege's theory. However, demand shocks in a job, rather than in an industry, are probably most relevant for this theory, and indeed the second column of table 9.9 shows a negative correlation between sectoral unemployment and the returns to experience. Finally, tenure is positively correlated with the returns to experience, particularly at the job-specific level.

TABLE 9.9 HERE

The rest of the results show that while there is evidence for these two alternative theories, the correlation between the returns to experience and the use of teams or job rotation is larger than the correlation of the returns to experience with unemployment or tenure, at least at the industry-specific level. I also include a measure of workplace unionization as this may affect the returns to experience or tenure. This might be because workers or firms invest more in training in such workplaces, or conversely, because the presence of unions compresses the wage distribution. Such firms might also be more likely to reject multitasking or teams as this may be viewed as a way to reduce employment as workers become better substitutes for each other. As table 9.9 shows, there is mixed evidence for these hypotheses. The correlation of the degree of unionization with industry returns to experience is small and positive while the correlation with job-level returns to experience is negative. One surprising result is that the correlation with multitasking is smaller for the job-level experience premium than for the industry premium. This might be because, as explained above, I have pooled 10 years' worth of wage data together in order to generate the industry-occupation-specific returns to experience.

Finally, I enter the level of multitasking directly into the wage regression, rather than using job dummies as indicated in the specification above, in order to get some idea of how much the use of multitasking might be contributing to the change in the returns to experience. I estimate the following equation:

$$lnw_{it} = b_0 + b_{11}School_i + b_{12}School_i^2 + b_{21}Exper_i + b_{22}Exper_i^2 + b_3 n_{it} + b_{41}School_i * n_{it} + b_{42}School_i^2 * n_{it} + b_{51}Exper_i * n_{it} + b_{52}Exper_i^2 * n_{it} + b_6 Dem_{it} + b_7 I_{it} + e_{it} \tag{9.3}$$

I use wage and individual data from 1983 through 1992, once again pooling these years together. The variable n_{it} is a measure of the extent to which multitasking work practices are used in individual *i*'s job in period *t*, measured as the percentage of firms in which at least half of the workers in the individual's job-type use each of the new work practices described earlier. The *n* variable is computed in various ways, including as the average diffusion in all the jobs that the worker was in during the 1983–1992 period and the diffusion in the job that the worker was in for the longest during the period. Due to the lack of multitasking data for years other than 1992, I must assume that the level of multitasking in a particular job *j* in period *t* is correlated with its level in 1992. If b_{51} in the above equation is estimated to be positive and significant, we can conclude that higher levels of multitasking are associated with higher returns to experience.

In addition to the variables discussed in the previous subsection, the wage regression also includes several variables that are suggested by alternative theories about the returns to experience. In particular, later cohorts may have larger returns to experience because they are less unionized and/or because they undertake more on-the-job training. To accommodate these possibilities, I_{it} in the equation (9.3) is a vector of job-level variables including the degree of unionization and the amount of training in individual *i*'s job in period *t*. I include the industry's unionization rate from Hirsch and McPherson (1993) and two additional measures of training: the degree of on-the-job training, taken from the NBER CPS January 1991 Supplement, and the degree of off-the-job training (firm-provided but off-site) from the Osterman survey itself.

Table 9.10 present the results from estimating the wage equation using ordinary least squares (OLS), where *n* (the proxy for multitasking) is measured as the average across all jobs for an individual from 1983 through 1992. The first two columns show the results for all individuals while the next two columns show the results for college graduates only.

TABLE 9.10 HERE

Both at the industry level and at the job level, the use of teams and job rotation increases the return to experience, while given the use of these work practices, cross-training reduces the return to experience. Many of these effects are statistically significant. For example, if the percentage of establishments in an industry using teams at the 50 percent level rises by 1 percentage point, then the returns to experience in that industry are estimated to rise by 0.02 percentage points. All the regressions shown include an interaction of industry-level unionization and training variables with years of experience. Thus, even if we allow for the fact that industries which use more teams or job rotation are also less unionized and tend to have a higher level of on-the-job and off-the-job company-provided training, there is still a positive effect of teams and job rotation on the returns to experience.

One explanation of this may be that so-called better jobs have a steeper experience-wage profile and tend to use more new work practices. However, this result holds even if we look at only college graduates. So to the extent that all college graduates have better jobs, the returns to experience seems to increase with multitasking even within those better jobs. Hence, there is reasonable evidence that industries that use more multitasking also have higher returns to experience.

A Final Look at the Effects of Unobserved Individual Heterogeneity

In this subsection, I consider the possibility that jobs with a greater use of teams and other new work practices show greater returns to experience because better learners choose these jobs. In particular, I study the effect of sorting using a two-stage fixed effects method as in Bartel and Sicherman (1999). I first estimate the following fixed-effect model:

$$lnw_{it} = b_0 + b_{11}School_i + b_{12}School_i^2 + b_{21}Exper_i + b_{22}Exper_i^2 + b_3 D_{it} + b_{41}School_i * D_{it} + b_{42}School_i^2 * D_{it} + b_{51}Exper_i * D_{it} + b_{52}Exper_i^2 * D_{it} + b_6 Dem_{it} + r_i + e_{it} \quad (9.4)$$

In the equation (9.4), D_{it} is a vector of dummy variables indicating the industry or industry-occupation (job) in which individual *i* works at time *t*, and r_i is a fixed individual effect. Next I regress the estimated individual premium from this first regression, $\hat{r}_i$, on the average level of multitasking in all the individual's jobs in 1983–1992 period and this average level is interacted with the individual's average schooling and experience across this time period in the following second-stage regression:

$$\hat{r}_i = \overline{J\bar{n}_i + m\bar{n}_i * \bar{\bar{H}}_i} + e_{it} \quad (9.5)$$

In equation (9.5), $\bar{n}_i$ is the average of the measure of multitasking (in 1992) for all jobs we observe for individual *i* in the data set, and H_i is a vector of the average of the individual's schooling and experience levels while s/he was in the sample. If the coefficients on any of these variables are significant, then this implies that there is sorting into jobs with different levels of multitasking on the basis of unobserved individual characteristics, which might be responsible for the correlation between the level of multitasking and the returns to experience.

The results for this second-stage equation are reported in table 9.11. First, almost none of the effects is significant. Since the second-stage regression includes an individual-level variable on the right-hand side and group-wide averages on the left-hand side, the standard errors may not be correctly estimated. However, it seems likely that if anything, the true standard errors will be bigger than those reported, so the results will remain insignificant. The coefficient on teams is small and negative at the industry level and there is a larger negative effect at the job level. The results are similar in size for job rotation, though the coefficients are now positive. These results seem to be suggesting that there is positive selection into jobs with more job rotation and negative selection into jobs with more teams. This is puzzling because it is the opposite of what we would expect if job rotation were indeed a proxy for bad jobs and teams a proxy for good jobs. The coefficient on TQM at the industry level is positive and almost significant, which is to be expected if more able people choose jobs with more new work practices, and this is also consistent with the positive estimated effect of cross-training. However, the estimated coefficients on PSG and SPC are negative at the industry level and the effect of SPC is negative at the job level as well. Taking these results together, there is mixed evidence for the hypothesis that positive selection into jobs with more new work practices explains why these jobs have higher returns to experience.

TABLE 9.11 HERE

Conclusion

In this chapter, I analyze whether the move toward new work practices involving multitasking may have changed the way in which wages grow over time for a particular worker. If more multitasking increases the returns to experience over a worker's lifetime, then workers in later cohorts will have higher returns to experience as more and more jobs start to involve multitasking. However, this may not be picked up right away if we only look at the returns to experience in a cross-section. If both starting wages and wage growth are higher for jobs with more multitasking (and therefore for later cohorts of workers), then it may appear in the cross-section as if the returns to experience have actually declined.

Using the PSID and data from an establishment-level survey conducted by Paul Osterman in 1992, I study the effects of multitasking on the returns to experience. I use the diffusion of various new work practices like teams and job rotation as proxies for multitasking and find that workers in jobs with a greater level of these work practices have higher within-job wage growth and returns to experience. The correlation between within-job wage growth and the use of teams is almost 0.04 for all workers and approximately 0.08 for young college graduate workers, and the correlation between the industry-specific returns to experience and the industry-specific level of teams is about 0.3. The returns to experience in a sector increase by about 0.02 percentage points when the percentage of firms using teams in the sector rises by 1 percentage point. I also find that later cohorts choose jobs with a greater amount of multitasking, and show that the differences in the experience premium across jobs cannot be fully explained by any of the alternative theories in the literature. I also present mixed evidence on the effect of positive selection into jobs that use more multitasking, which implies that it is possible that jobs with more multitasking may have higher returns to experience at least in part because workers in such jobs have higher unobserved ability.

Anecdotal evidence suggests that the increase in multitasking has been driven by changes in technology, particularly cheaper computing power. In Autor et al. (2002 and Baker and Hubbard (2003), it is clear that it was the advent of computers that led to a change in work organization. This chapter then provides a previously overlooked link between technological change and the returns to experience, through the reorganization of jobs.

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Table 9.1 Diffusion of work practices

Work practice	Some use		At least 50% use	
	All (%)	Manufacturing (%)	All (%)	Manufacturing (%)
Teams	54.50	50.10	40.50	32.30
Job rotation	43.40	55.60	26.60	37.40
TQM	33.50	44.90	24.50	32.10
Quality circles	40.80	45.60	27.40	29.70
None	21.80	16.00	36.00	33.20

Source: Reproduced from Osterman (1992).

Notes: "Some use" refers to the percentage of establishments in each industry listed in 3-digit Standard Industrial Classification (SIC) in which at least some employees were involved in the work practice, and "At least 50% use" refers to the percentage of establishments in each industry in which at least 50 percent of all core employees are involved in respective work practice.

Table 9.2 Correlation between work practices (at the establishment level)

	Teams	Job rotation	Cross-training
Teams	1		
Job rotation	0.1548	1	
Cross-training	0.13	0.395	1
Whether job more complex	0.0073	−0.0155	0.0173

Source: Author's computations from Osterman's 1992 data.

Notes: The variables under analysis are the establishment-level binary responses to the following question for each work practice: "Do more than 50 percent of core employees use the work practice?"

Table 9.3 Definition of cohorts in PSID (1970–1992)

Cohort	Labor market entry	Maximum period observed
1	1933–1937	1970–1977
2	1938–1942	1970–1982
3	1943–1947	1970–1992
4	1948–1952	1970–1992
5	1953–1957	1970–1992
6	1958–1962	1970–1992
7	1963–1967	1970–1992

8	1968–1972	1970–1992
9	1973–1977	1973–1992
10	1978–1982	1978–1992
11	1983–1987	1983–1992

Table 9.4 Effect of experience on wages by labor market entry cohort and schooling level, 1970–1992: Least squares regression results

Schooling level (yrs.)	1958–1962	1963–1967	1968–1972	1973–1977	1978–1982	1983–1987
< 12	1.55	1.41	4.11	2.01	3.22	5.22
	(0.011)	(0.008)	(0.006)	(0.008)	(0.016)	(0.033)
12	1.92	2.65	4.95	1.89	6.21	7.50
	(0.011)	(0.008)	(0.006)	(0.008)	(0.016)	(0.033)
13–15	2.56	2.92	4.87	1.90	7.35	7.51
	(0.011)	(0.008)	(0.007)	(0.009)	(0.017)	(0.040)
16	3.09	3.59	5.31	3.46	8.76	8.79
	(0.012)	(0.009)	(0.007)	(0.009)	(0.017)	(0.040)
> 16	2.56	3.50	6.25	4.12	8.95	6.08
	(0.012)	(0.009)	(0.007)	(0.010)	(0.017)	(0.040)
R^2	0.22	0.26	0.23	0.27	0.35	0.22

Notes: 100 × (estimated coefficients) are reported, with standard errors in parentheses. The estimates reported in each column come from a separate regression.

Table 9.5 Average level of new work practices, as measured in 1992, in sectors chosen by successive cohorts of labor market entrants (high school graduates)

Cohort	Teams	Job rotation	TQM	PSG
1973–1977	41.72	30.67	31.53	35.92
1978–1982	37.86	26.07	36.98	32.23
1983–1987	35.08	41.9	40.3	22.65

Table 9.6 Average level of new work practices, as measured in 1992, in sectors chosen by successive cohorts of labor market entrants (college graduates)

Cohort	Teams	Job rotation	TQM	PSG
1973–1977	48.14	4.02	38.22	20.54
1978–1982	51.7	5.08	49.63	29.54
1983–1987	53.81	1.11	64.66	16.27

Table 9.7 Correlation between education, experience, and the use of new work practices

Work practice	Schooling	Experience	Experience *college	Experience*High school
Teams	0.14	−0.11	−0.07	−0.08
Job rotation	−0.11	−0.02	−0.02	−0.02
PSG	0.05	−0.09	−0.10	−0.07
SPC	0.10	−0.09	−0.11	−0.03
TQM	0.13	−0.09	−0.04	−0.02
Cross-training	−0.06	−0.05	−0.10	−0.04

Notes: The variables used - in the work practice column are job-level multitasking measures (% establishments in each industry in which at least 50% of all core employees are involved in each work practice).

Table 9.8 Correlation between within-job wage growth and the use of new work practices

Work practice	All	High school		College	
		Experience < 10 yrs.	Experience > 20 yrs.	Experience < 10 yrs.	Experience > 20 yrs.
Teams	0.036	0.001	0.027	0.081	0.010
Job rotation	−0.001	0.022	−0.004	0.001	−0.004
PSG	0.009	0.006	−0.013	−0.003	0.005
SPC	0.020	−0.004	−0.011	0.030	0.005

TQM	0.039	0.019	0.001	0.066	0.007
Cross-training	−0.003	0.017	−0.013	−0.022	−0.006

Notes: The variables used on the vertical axis in the work practice column are job-level multitasking measures (% establishments in each industry in which at least 50% of all core employees are involved in each work practice).

Table 9.9 Correlation between estimated sector-specific experience premia and sector-level variables

	Industry specific	Job specific
Teams	0.297	0.053
Job rotation	0.449	0.010
Off-the-job training	0.207	0.174
Unions	0.055	−0.249
Unemployment	0.134	−0.393
Tenure	0.059	0.159

Table 9.10 Results of OLS estimation of the wage equation, run separately by schooling level

Work practice	All		College	
	Industry level	Job level	Industry level	Job level
Teams	−0.0018	−0.0059	−0.0019	−0.0074
	(1.30)	(3.94)	(0.97)	(3.99)
Job rotation	−0.0038	−0.0001	−0.0047	0.0372
	(1.75)	(0.01)	(1.40)	(1.52)
Cross-training	0.0087	0.0046	0.0071	0.0017
	(5.22)	(2.23)	(2.90)	(0.65)
Teams × experience	0.0002	0.0008	0.0002	0.0009
	(1.57)	(4.66)	(0.79)	(3.99)
Job rotation × experience	0.0006	0.0003	0.0006	0.0003
	(2.65)	(0.64)	(1.40)	(1.74)
Cross-training × experience	−0.0009	−0.0007	−0.0005	4E−6

	(4.93)	(2.64)	(1.60)	(0.67)

Notes: The regression also includes years of schooling and years of experience, separately and in interaction, as well as demographic variables and other industry-level variables as explained in the text. Absolute t-statistics are in parentheses.

Table 9.11 Results from second stage of two-stage fixed effects regression

Work practice	Industry level	Job level
Teams	−0.009 (0.019)	−0.035 (0.026)
Job rotation	0.007 (0.008)	0.059 (0.036)
TQM	0.034 (0.019)	−0.006 (0.075)
PSG	−0.045 (0.024)	0.054 (0.033)
SPC	−0.016 (0.013)	−0.054 (0.031)
Cross-training	0.037 (0.020)	0.002 (0.050)

Note: Standard errors are in parentheses.

[1] For a definition of Taylorism, see Encyclopaedia Britannica, http://www.britannica.com/EBchecked/topic/1387100/Taylorism.

[2] In a more recent paper, Osterman (2006) finds that high-performance work practices like teams and job rotation are associated with higher wages, both for blue-collar manufacturing workers and for their managers.

[3] For more details on the survey, see Osterman (1994).

[4] The 1997 follow up to this survey did ask about wages but it still did not contain detailed information on individual characteristics.