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MULTI-TASKING AND THE RETURNS TO EXPERIENCE

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Multi-tasking and the Returns to Experience*

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Abstract

In this paper, I study how an increase in the use of new work practices that involve multi-tasking has affected the returns to experience. If each task in a job has a concave learning curve, then increasing the number of tasks may increase the returns to experience. Using the Panel Study of Income Dynamics, I provide evidence for the fact that successive cohorts have greater returns to experience. Next, I construct proxies for multi-tasking using Paul Osterman's 1992 survey of workplace practices in U.S. establishments, and find that (i) later cohorts choose jobs with greater multi-tasking, (ii) the rate of within-job wage growth rises with the degree of multi-tasking, and (iii) the returns to experience are larger in jobs with more multi-tasking . Finally, I find mixed evidence on the effect of unobserved heterogeneity, which implies that part of these larger returns to experience may be because those in jobs with more multi-tasking have higher unobserved ability.

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1 Introduction

This paper studies how recent changes in the organization of work, namely the move towards multi-tasking, has changed 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 differences in the wages of older workers and 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 to 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 paper is that for those entering the labour market in the late 1960s and early 1970s, wage growth over the first 10 years in the labour market was lower for college graduates than for high school graduates, while for those who entered in the late 1980s, the wage growth over the first ten years for college graduates increased so that it was almost as high as that of high school graduates (Aaronson, 2001).

I analyze whether the change 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 towards more multi-tasking and less specialization. If wages increase with experience on the job because workers are learning how to do each task better, then a move towards more multi-tasking implies that each year of experience in a job is equivalent to less actual time spent working on each different task. The returns to an additional year on the job equals 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 multi-tasking. We may also observe lower starting wages with more multi-tasking (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 (hence Katz and Murphy's observation above). So if the returns to experience in the cross-section are interpreted as a way to predict how much today's young workers will earn when they are older, in a situation with changes in the level of multi-tasking, this interpretation would be misleading.

In the next section, I review the literature on the returns to experience, and why it might differ according to industry or type of job, as well as how technical change might affect it. After that I describe the spread of new work practices including multi-tasking. In the fourth section, I describe the data on multi-tasking, including a discussion on the proxies used for multi-tasking, and the methods used to construct a measure of multi-tasking for each worker in our wage dataset. Section five presents the main results and some robustness checks, and Section six concludes.

2 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 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 return to experience. In fact, intuititively, it appears that clear that new technology should be complementary to young (and more flexible) workers, rather than older workers. My argument in this paper is that technical change has affected the organization of work, which in turn has affected the wage growth over a worker's lifetime.

There are a few other papers in the literature which explain 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 favorable shock will have a steeper wage-experience profile. 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 a small literature on job-specific experience which 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 which address the reorganization of work explicitly. They derive conditions under which a firm will switch from a Tayloristic mode of production to multi-tasking. This happens if the tasks become more complementary in production, there is more learning spillovers between tasks, or workers have more flexible human capital. However they do not directly address the effects on the returns to experience.

Most of the literature on multi-tasking, and the reorganization of work in general, study its causes, the importance of classic economic problems like free-riding under the new form of work organization, and the increase in total output due to the introduction of the new work practices. This paper contributes to this literature by analyzing how productivity changes over a worker's lifetime under the new work organization. The fact that less repetition in a task may lead to faster learning in 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. This paper 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 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. If technical change facilitates multi-tasking, 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. This 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 the within cohort returns. 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 Section 1, it seems that the cross-sectional returns to experience have increased for high school graduates, and not for the 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 is also consistent with Aaronson's (2002) findings, and with the evidence in the next section about how multi-tasking has affected both blue-collar and white-collar workers, but in slightly different ways.

3 The Increasing Importance of Multi-tasking

Empirical evidence suggests that this kind of a change in the organization of jobs - the move towards more multi-tasking - 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.

3.1 Case Studies

Manufacturing — Studies on the automobile industry are especially interesting since this sector was the basis for the Fordist model of assembly line manufacture, the standard post-Industrial Revolution structure of specialization. Yet several firm-level studies show significant movement away from this kind of organization towards a less specialized, more multi-tasking 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 material 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 like a standard mass production set-up, 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 Massachussets where employment fell by 50% in the early 1980s, accompanied by movement towards a flatter hierarchy and increased use of teams. This may imply that any increase in productivity associated with more teams might actually be due to unproductive workers being laid off concurrently with the increase in the use of teams. This is something that we need to keep in mind for the 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 the services are harder to come by. Autor, Levy and Murnane (2001) present an interesting case where the introduction of a new technology led to multi-tasking 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, and it was here that the new userfriendly technology led to multi-tasking. This may also be the kind of mechanism behind Baker and Hubbard's (2003) finding in the truck industry. They find that the introduction of some on-board computers lowered the costs associated with complex job design and therefore led to greater multitasking, while other on-board computers which provide location information and real-time communication actually led to more specialization. Citibanks' organization of work units around particular markets is another example (Applebaum and Batt, 1994). Each manager controls an entire transaction for a particular group of customers, and the jobs of front-line workers were expanded to allow them to handle all the steps necessary for a customer request. The change from mainframes to mini-computers facilitated this change in job design. Applebaum 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, in counties that have larger average establishment size in contruction, manufacturing, transportation, utilities or financial services. Moreover, lawyers tend to be less specialized in counties where the share of employment in manufacture and wholesale trade is low. Garicano and Hubbard's main interest is in analyzing the condition 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 on the trend in specialization. Kendall (2002) finds that Ph.Ds from better departments tend to do less specialized research than Ph.Ds employed in the same department but who graduated from lower-ranked departments, showing that higher ability workers may specialize less.

One issue that we should keep in mind when we think of highly skilled jobs is that workers in these jobs have highly specialized education. So multitasking across disciplines within economics, for example, is probably more difficult, or requires more re-training, than multi-tasking across machines on the shop floor. Moreover, suppose we consider knowledge to be the output in academia, and it can be produced by either teaching or research. Each of these tasks are composed of several sub-tasks, e.g., research comprises publications in different fields of economics, which may be considered to be substitutes. In particular, 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, multi-tasking leads to each worker performing more tasks, but this does not happen if the tasks are complementary.

3.2 The Diffusion of New Work Practices

What is the magnitude of this reorganization of work in the U.S. economy? Using the survey data I use later in this paper, 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 is it that flexible work practices, like teams will be adopted.[1] Ichniowski, Shaw and Prennushi (1997) surveyed 36 U.S. 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% participate in more than one team and just under 10% are involved in job or task rotation. Ben-Ner et al. (2001) study a sample of 800 firms in Minnesota and show that over 40% of these firms had some use of individual-based decision-making participation and a similar proportion used some group-based decision-making participation like teams and quality circles. In a survey of approximately 300 large U.S. firms carried out in the mid-nineties, 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% of all managers in Britain said that organizational change affecting nonmanual jobs had widened the range of tasks performed, while for manual jobs the relevant figure was about 40% (Caroli and van Reenen, 2001).

4 Data

4.1 New Work Practices and Multi-tasking

Before I present the results, in this section, I describe the multi-tasking data. I use a unique dataset that comes from a 1992 survey[2] 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 having such a respondent and surveying 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 say in a big firm with multiple locations. The response

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

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

rate was 65%.

The final sample consists of 806 establishments which had 50 or more employees and were in non-agricultural industries. The occupation group that Osterman focused on was those in "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 restricted to studying 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 mangement (TQM). Interviewees were asked whether each of these practices were used at their establishments, and if so, what percentage of core employees were involved. They were also asked whether employees participated in any amount of cross-training. i.e., training on various machines or various parts involved in a job.

I use each of these work practices separately as proxies for multi-tasking, and also look at the effect of cross-training. I also examine the effects of including only teams, job rotation and cross-training in this proxy. How well do these work practices proxy for the kind of multi-tasking I have described in the introduction? Hamilton, Nickerson and Owan (2002) describe the transition of a garmet facility run by the Koret Corporation from a traditional Taylorist production setup to a team or module production setup. In the traditional system, the sewing operation was broken up into between 10 and 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 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

Work Practice	**Some**	**Use**	**At Least**	**50%**
	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%

Table 1: Diffusion of Work Practices (Reproduced from Osterman, 1992). Notes: "Some Use" refers to the percentage of establishments in each 3 digit SIC industry in which at least some employees were involved in the work practice and "At Least 50 percent" refers to the percentage of establishments in each industry in which at least 50 percent of all core employees are involved in each work practice

what is essential for the multi-tasking theory presented here is that workers acquire experience on more tasks or machines that they did under the traditional assembly line setup. For example, in Hamilton et al.'s description, a strip of the assembly line has essentially been shaped into a U, so that instead of being exposed only to 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 multi-tasking in theory, the empirical studies show that the diffusion of teams is a reasonably good proxy for the movement away from specialization and towards multi-tasking. Of course, there may be, for example, 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 multi-tasking.

It is probably less controversial to interpret job rotation as multi-tasking. It is not immediately clear how SPC and TQM would amount to multi-tasking, 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 1 shows the diffusion of the new work practices in the economy and in the manufacturing sector in particular. The first two columns show the

	Teams	Job Rotation	Cross-training
Teams	1		
Job Rotation	0.1548	1	
Cross-training	0.1300	0.3950	1
Whether Job More Complex	0.0073	-0.0155	0.0173

Table 2: Correlation between work practices (at the establishment level). Notes: Variable used is "do more than 50 percentage of core employees use the work practice". Author's computations from Osterman's data

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% of the employees in core jobs were involved in the work practice in question (*the intensive margin*). Most importantly, nearly 80% of all establishments were involved in one or more of these new work practices, and this proportion rises to nearly 85% for manufacturing establishments. Among these, 50% of manufacturing establishments were involved in teams, as were nearly 55% 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. If we look at the third and fourth column, it is clear that a significant proportion of these establishments have half or more of their core employees participating 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 (more than 32% of manufacturing establishments have at least 50% 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, establishments which use these teams or quality circles intensively also tend to use more cross-training. As Table 2 shows, at the intensive margin, establishments which use more teams, do tend to use more job rotation and cross-training as well. So, any finding that jobs with higher use of teams also have higher returns to experience may be explained by the fact that worker in these jobs acquire more training, in particular, cross-training. The respondents in Osterman's survey were also asked whether skills involved in the core job in their establishment have become more complex in the last few years. The last row of Table 2 shows that the core job in establishments which use more teams has 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 multi-tasking, though these effects are small and perhaps not very convincing. The second observation may indicate that the interpretation of teams and job rotation as multi-tasking differs according to the kind of job, as explained next.

One final source of ambiguity concerning the interpretation of these work practices as evidence of multi-tasking involves the distinction between job rotation and the use of teams. In particular, since tasks are often shared or rotated within teams, some respondents may use these terms interchangeably. In addition, a work practice resembling both the use of teams and job rotation may be labelled as "teams" in better jobs, and "job rotation" in worse jobs. Osterman finds that the percentage of manufacturing establishments with blue collar core workers - the so-called bad jobs - which use teams only, is almost equal to the percentage which uses both teams and job rotation. Moreover, more than 14% of non-manufacturing establishments where core workers are not blue collar use teams only, while less than 6% of blue collar manufacturing establishments use teams only. Similarly only 7% of the former use job rotation only while nearly 12% of the latter use job rotation only. These figures imply two important issues 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. Moreover, the use of either teams or job rotation may act as a better measure of multi-tasking than each work practice separately.

4.2 Wages and individual characteristics

The main problem with using this new work practices data to test the effects of multi-tasking on wages, is that this dataset does not include data on wages or individual characteristics.[3] To get this information, I use annual data from the Panel Study of Income Dynamics (PSID). This dataset contains demographic and other information on about 6000 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 dataset used in the following regressions consists of white males with

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

upto 40 years of experience, who are heads of household and who are either working, temporarily laid off or are looking for work. Following the literature, only those who worked for 1500 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 log hourly real wages, where the wages are deflated by the CPI (1982-84 = 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 the two of the most important variables, years of schooling and age, according to the procedure outlined in Lillard (2001). Because the multi-tasking data refers to only those in "core" jobs, that is, only non-managerial, non-supervisory workers, I use only these workers for the regressions in which I test the connection between multi-tasking and wages. These regression also includes time dummies, in order to control for economy-wide effects.

5 Empirical Strategy

I start by investigating whether the second stylized fact referred to in the introduction - namely that successive cohorts have different returns to experience over their lifetime - is in fact true 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 can correlate wage growth within a job for those who did not change jobs in the dataset, with the job-level measure of multi-tasking. This gives us some idea about the difference in wage growth across jobs, and its relation to the level of multi-tasking in a job. Finally, I directly study whether multi-tasking is associated with higher returns to experience by estimating the returns to experience by industry (or industry-occupation) and correlating these to the level of multi-tasking in that industry (or industry-occupation). I also estimate a wage regression which includes the level of multi-tasking interacted with the level of work experience and discuss the issues raised by unobserved individual heterogeneity.

5.1 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, i, in the PSID sample

Cohort	Labor Market Entry	Maximum Period Observed
1	1933-1937	1970-77
2	1938-1942	1970-82
3	1943-1947	1970-92
4	1948-1952	1970-92
5	1953-1957	1970-92
6	1958-1962	1970-92
7	1963-1967	1970-92
8	1968-1972	1970-92
9	1973-1977	1973-92
10	1978-1982	1978-92
11	1983-1987	1983-92

Table 3: Definition of Cohorts in PSID (1970-1992)

described in Section 4.2 (not just those in "core" jobs), to check whether this data gives results about cohort effects on the return to experience that are similar to Aaronson's (2001):

$$\begin{aligned}\ln w_{it} &= \beta_0 + \beta_{11} School_i + \beta_{12} School_i^2 + \beta_{21} Exper_{it} + \beta_{22} Exper_{it}^2 + \beta_3 Cohort_i \\ &\quad + \beta_{41} School_i * Cohort_i + \beta_{42} School_i^2 * Cohort_i + \beta_{51} Exper_{it} * Cohort_i \\ &\quad + \beta_{52} Exper_{it}^2 * Cohort_i + \beta_6 Dem_{it} + \varepsilon_{it}\end{aligned}$$

where $School$ measures the years of schooling and $Exper$ measures potential labor market experience, $Cohort$ is a cohort dummy, and Dem is a vector of other individual characteristics like union membership, marital status, and geographical region. In addition to the variables already mentioned, I also include the economy-wide unemployment rate at t. In this section, my objective is to document the cohort effect on the returns to experience. Clearly there are factors other than the level of multi-tasking in a job which vary across cohorts, so that the cohort effect captures the total effect of all these factors. In the following sections, I analyze whether the worker's choice of industry - and therefore level of multi-tasking - can be interpreted as explaining these inter-cohort changes. In the above wage equation, if the estimate of β_{51} is significant, this means that the returns to experience vary by cohort.

I divide the individuals into cohorts according to when they entered the labor market (as noted in Section 4.2, the PSID data I use runs from 1970 to 1992). A worker with 12 years of education who is 40 years old in 1980 entered the labor market in 1959, as did a worker with 16 years of education who is 44 in 1980. So these two workers are in the same cohort. I construct five year cohorts so that all those who entered the labor market between 1923 and 1927 are in one cohort, all those who entered between 1928 and 1932 are in the next cohort, and so on. There are 14 such cohorts. Dropping the two oldest and the youngest cohorts to make sure there are enough observations in each cohort, I have 11 cohorts in the final dataset. Table 3 summarizes the definition of the cohorts. It may seem like it will be difficult to disentangle the cohort and potential experience effects in the above regression. However as Table 3 shows, there is some variation in experience within each cohort groups at a point in time. Moreover, e.g., I have observations for experience levels between 0 years and 14 years for all of the cohorts 8, 9, and 10, which means that I can estimate the wage growth between years 0 and 14 for each of these cohorts, and compare them to see whether there is any cohort difference in the returns to experience.

Table 4 reports the results from this wage regression. The coefficient reported is the return 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 1973-77 cohort, 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). So the higher returns to experience could be observed if there has been a change in the quality of education, a change in the actual work experience (given potential experience), or because the price of either of these skills have changed for later cohorts. One last point to note is that we only have multi-tasking data for non-supervisory, non-managerial workers, so we will only be able to comment on the effect of multi-tasking on the wages of these workers. Of course in the college graduate group, there will be some professionals who are not managers, so we can address any changes in their returns to experience as well.

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 multi-tasking. That is, do later cohorts choose jobs with a greater number of tasks and does this job choice lead to higher wage growth? According to the literature on multi-tasking, new "complex" jobs have been created in the last two decades, partly by means of reorganiza-

Schooling Level	**1958-1962**	**1963-1967**	**1968-1972**	**1973-1977**	**1978-1982**	**1983-1987**
< 12 years	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 years	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 years	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 years	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 years	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

Table 4: Effect of Experience on Wages by Labor Market Entry Cohort and Schooling Level, 1970-92: Least Squares Regression Results. Notes: Estimate coefficients*100 are reported, with standard errors in parentheses

tion of existing jobs. Unfortunately, we do not have the individual data to observe reorganization at this level of disaggregation. From the description of the data in Section 4, it is clear that we have on the one hand, wage and individual characteristics for each worker, and measures of multi-tasking for each establishment, but since these data sources cannot be matched, I do not have measures of multi-tasking attached to each worker. In order to connect a worker with a measure of multi-tasking, I aggregate these measures from the establishment level up to the 3 digit SIC industry level. I then assign each worker a level of multi-tasking according to their current (that is, in 1992) industry, or current industry-occupation pair. The two measures of multi-tasking I focus on are the percentage of establishments in each 3 digit SIC industry in which at least 50 % of the core employees were involved in the work practice (*industry-level multi-tasking*), and the percentage of establishments in each industry in which at least 50 % of the employees in a particular SOC 1-digit occupation are involved in each work practice (*job-level multi-tasking*). So for a particular worker, the first measure focuses on what percentage of establishments in her industry use multi-tasking, but not necessarily on whether that use is by workers in her occupation. The second measure is narrower - it focuses on what percentage of establishments in this

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 5: Average 1992 Level of New Work Practices in Sectors Chosen by Labor Market Entrants (High School 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 6: Average 1992 Level of New Work Practices in Sectors Chosen by Labor Market Entrants (College Graduates)

worker's industry have core jobs in her particular occupation and also use multi-tasking. In other words, the first measures relates to the probability that multi-tasking is occuring somewhere in the worker's industry, while the second relates to the probability that it is occuring in her occupation. Not all SOC occupations are represented in the core jobs in the work practices data, which means than we can use this second measure only for a smaller number of workers. Since we have information on each individual's industry and occupation of employment in each year from the PSID data, and since the multi-tasking literature points out that there are significant sectoral differences in the degree of reorganization, the next step of this part of the empirical analysis is to check whether there are inter-sector differences in the returns to job tenure and experience and how it relates to inter-sector differences in the level of multi-tasking.

5.2 Cohort effects in choice of sector

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

As noted earlier, we only have work practices data for 1992. So we cannot directly measure the difference in the level of multi-tasking in the jobs chosen by labour market entrants of different cohorts. Instead we will look at whether there are systematic differences in choice of sector by the level of multi-tasking in 1992. For three cohorts, we have wage data from their labour market entry to 1992. I first assigned each individual an industry-level of multi-tasking based on the sector in which they had their first job, rather than their current job. For each cohort, I averaged the industry-level measure of multi-tasking over all individuals in that cohort. Tables 5 and 6 show these results for high school and college graduates, respectively. So for the 1973-77 cohort, the typical sector chosen for a first job by a college graduate had nearly 42% 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 1983-87 cohort had nearly 54% of establishments involved in teams in 1992. According to this, college graduates in the later cohorts were entering sectors which had a larger percentage of establishments involved in teams in 1992. That is, a college graduate entering the labour market in 1983-87 is more likely than a college graduate in an earlier cohort to start off in a sector that will be using teams in 1992. This is clearly not true for high school graduates.

It is safe to assume that when the 1973-77 college graduate cohort entered the market, there was little use of teams anywhere. So if we found that for this cohort the wage growth in the first ten years is higher for those who chose sectors that had greater multi-tasking in 1992, this may be because of some characteristic of the sector, which also made this sector more likely to have teams in 1992. This can be interpreted as evidence that there is no causal relation between the level of multi-tasking and wage growth. The final observation is that the sectors where college graduates have their first job are quite unlikely to have job rotation - which maybe another indication that job rotation is a proxy for a bad job - and this number falls for later cohorts.

5.3 Multi-tasking and Wage Growth Within a Job

One way to see whether multi-tasking is associated with higher wage growth is to compute the increase in wages within a job and correlate that to the job-level measure of multi-tasking. Before that, it is instructive to see how the

Work Practice	**Schooling**	**Experience**	**Experience**	
			College	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

Table 7: Correlation between Education, Experience and the Use of New Work Practices. Notes: The variable used here is job-level multi-tasking, the percentage of establishments in each industry in which at least 50 percent of all core employees are involved in each work practice

use of multi-tasking correlates with the average characteristics of workers in a sector. Table 7 shows the correlation between the use of the work practices at the industry-occupation level, and the industry-occupation level average individual characteristics from the PSID. Since the multi-tasking data are from 1992, I compute the average schooling level and experience level by industry-occupation group in 1990-92 from the PSID (I pool these three years to increase the number of observations). Sectors with a higher average level of education tend to have more extensive use of teams, but less use of job rotation. This again may be interpreted as evidence 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 we are looking at one point in time, the younger workers in this period are those belonging to a later cohort. Therefore, this implies that there is greater use of teams and job rotation among later cohorts.

Next, I test whether wages rise faster in jobs with greater multi-tasking. Since the PSID is a panel, I can track individuals' wages over time. For this part, 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. Since the measures of multi-tasking are only available for 1992, I assume that the level of multi-tasking in 1983 is zero. This is fairly consistent with anecdotal evidence on the rise of new work practices, So then the level of multi-tasking in 1992 also represents the change in the degree of multi-tasking in the preceding 10 years. I correlate this at the industry-occupation

Work Practice	**All**	**High School** Exp < 10 Yrs	Exp > 20 Yrs	**College** Exp < 10 Yrs	Exp > 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

Table 8: Correlation between Within-Job Wage Growth and the Use of New Work Practices. Notes: The variable used here is job-level multi-tasking (the percentage of establishments in each industry in which at least 50 percent of all core employees are involved in each work practice)

level to the within-job wage growth over these 10 years. Table 8 presents these results.

The main observation from Table 8 is that jobs with greater use of teams have higher within-job wage growth both overall as well as within schooling and experience groups. The correlation is smallest among young high school graduates, but is as high as 8% 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 shows that, consistent with this story, job rotation raises wage growth for young high school graduates more than for anyone else. Also, cross-training increases wage growth for young high school graduates but reduces it for older high school graduates and all college graduates. These two results imply that job rotation and cross-training may act as proxy for relatively "bad" jobs - CEOs don't rotate between jobs or even train on multiple machines, or at least, what they do is not labelled job rotation or cross-training - which may bias the estimated coefficients of the wage regression. Finally, both SPC and TQM seems to have a positive effect on the wage growth of young workers, while participation in PSG lowers the wage growth of older high school graduates. It is important to remember that these results hold only for those who have been in the same job from 1983-92, and so may not be extrapolated to job changers. In Section 5.5, I present some results on those who change industry-occupation combinations in this period to discuss the effects of unobserved individual heterogeneity.

5.4 The Returns to Experience and Multi-tasking

The results presented so far indicate that there is a correlation between the level of multi-tasking in a sector and the level and growth in wages in that sector. One problem with the results in Section 5.3 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 multi-tasking. 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:

$$\begin{aligned} \ln w_{it} &= \beta_0 + \beta_{11} School_i + \beta_{12} School_i^2 + \beta_{21} Exper_{it} + \beta_{22} Exper_{it}^2 \\ &\quad + \beta_3 D_{it} + \beta_{41} School_i * D_{it} + \beta_{42} School_i^2 * D_{it} \\ &\quad + \beta_{51} Exper_{it} * D_{it} + \beta_{52} Exper_{it}^2 * D_{it} + \beta_6 Dem_{it} + \varepsilon_{it} \qquad (1) \end{aligned}$$

where D_{it} is a vector of dummy variables indicating the industry (or industry-occupation) in which individual i works at time t (so the D's are job-number dummies, and the excluded industry-occupation pair is construction-production). I correlate these estimates with the sector-level of multi-tasking to see whether the returns to experience are indeed higher in sectors with more multi-tasking. It is important to note again that the multi-tasking measures are only available for 1992. As in the previous section, the wage and other individual data is from 1983 to 1992. As before, I include the economy-wide unemployment level for each year. For the industry-occupation level, I pool the wage and individual data from 1983-92 together to make sure that I have enough observations (as explained in Section 5.1, not all occupations are represented in the core jobs, so the number of observations for the industry-occupation level is much smaller than for the industry level). In Table 9, I correlate the industry-specific (and "job" or industry-occupation specific) returns to experience to the level of multi-tasking in that industry or job in 1992.

Since I am measuring the industry- or industry-occupation level returns to experience, I need to check the multi-tasking theory against other theories explaining inter-industry differences in the returns to experience. According

	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: Correlation between Estimated Sector-Specific Experience Premium and Sector-Level Variables

to Helwege (1992), the returns to experience will be higher in sectors which face a positive demand shock. I use the sector-level unemployment rate as a proxy for sectoral demand. Neal (1998) implies that sectors with higher returns to experience should also have higher average levels of tenure. In order to allow for these theories, I also include the sector-level of unemployment (a proxy for demand) and the sectoral average level of tenure. The first column in Table 9 presents the correlation between the industry-specific experience premium and the work practice and other industry-level variables, while the second column shows the 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 relevant for this theory. Indeed, the second column shows a negative correlation between sectoral unemployment and the returns to experience. Similarly, tenure is positively correlated with the returns to experience particularly at the job-specific level.

The rest of the results are similar, and show that while there is evidence for these two alternative theories, the correlation between returns to experience and teams or job rotation is larger than the correlation with unemployment or tenure, at least for at the industry-specific level. One surprising result is that the correlation with multi-tasking is smaller for the job-level experience premium than the industry premium. However this might be because, as explained above, I have pooled 10 years wage data together for the industry-occupation level.

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

$$\begin{aligned}\ln w_{it} &= \beta_0 + \beta_{11} School_i + \beta_{12} School_i^2 + \beta_{21} Exper_{it} + \beta_{22} Exper_{it}^2 + \beta_3 n_t \\ &\quad + \beta_{41} School_i * n_{it} + \beta_{42} School_i^2 * n_{it} + \beta_{51} Exper_{it} * n_{it} + \beta_{52} Exper_{it}^2 * n_{it} \\ &\quad + \beta_6 Dem_{it} + \beta_7 I_{it} + \varepsilon_{it} \qquad (2)\end{aligned}$$

I use wage and individual data from 1983-1992 (once again, I pool these years together for the industry-occupation level). The variable n_{it} is a measure of the extent to which multi-tasking work practices are used in individual i's job in period t. n is a vector containing 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, e.g., as the average diffusion in all the jobs that the worker was in during the period, and the diffusion in the job that the worker was in for the longest during the period. It is useful to note here that I only have data on n for 1992, so I am assuming that the level of multi-tasking in a particular job j in period t is correlated with its level in 1992. In the results in Table 10, the regression is estimated separately using each work practice.

If β_{51} is positive and significant, we can conclude that higher levels of multi-tasking are associated with higher returns to experience. I_{it} is a vector of job-level variables like the degree of unionization, amount of training, etc in individual i's job in period t.

Finally, in addition to the variables discussed in the previous section, the wage regression also includes several variables which 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 because they undertake more on-the-job training. Therefore, 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 from the CPS January 1991 Supplement and the degree of off-the-job training (firm-provided but off-site) from the Osterman survey itself - in the regression.

Table 10 present the results from the OLS estimation of the wage equation. The measure of n used here is the average over all jobs in 1983-1992. The first two columns show the results for all individuals while the next two columns show the results for college graduates. Both at the industry- 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

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)

Table 10: Results of OLS estimation of wage equation by schooling level. Notes: The regression also included years of schooling and year of experience, separately and in interaction, as well as demographic variables, and other industry-level variables (absolute t-statistics in parentheses)

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)
Problem-Solving Groups	-0.045 (0.024)	0.054 (0.033)
Statistical Process Control	-0.016 (0.013)	-0.054 (0.031)
Cross-training	0.037 (0.020)	0.002 (0.050)

Table 11: Results from Second-Stage of Two-Stage Fixed Effects Regression (standard errors in parentheses)

the return to experience. For example, if the percentage of establishments in an industry using teams at the 50% level rises by 1, then the return to experience in that industry will rise by 0.0002. 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, the result holds even if we look within college graduates. So to the extent that all college graduates have better jobs, the returns to experience seems to increase with multi-tasking even within those better jobs. Hence, there is significant evidence that industries which use more multi-tasking also have higher returns to experience.

5.5 A final look at the effects of unobserved individual heterogeneity

In this section, I consider the effect of the fact that jobs with greater use of teams etc. may 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:

$$\begin{aligned}\ln w_{it} &= \beta_0 + \beta_{11} School_{it} + \beta_{12} School_{it}^2 + \beta_{21} Exper_{it} + \beta_{22} Exper_{it}^2 \\ &+\beta_3 D_{it} + \beta_{41} School_{it} * D_{it} + \beta_{42} School_{it}^2 * D_{it} \\ &+\beta_{51} Exper_{it} * D_{it} + \beta_{52} Exper_{it}^2 * D_{it} + \beta_6 Dem_{it} + \rho_i + \varepsilon_{it} \ (3)\end{aligned}$$

where D_{it} is a vector of dummy variables indicating the industry or industry-occupation ("job") in which individual i works at time t and ρ_i is a fixed individual effect. Next I regress the estimated individual premium $\widehat{\rho}_i$ on the average level of multi-tasking in all the individual's jobs in 1983-1992 and this average level interacted with schooling and experience in the following second-stage regression:

$$\widehat{\rho}_i = \eta \overline{n_i} + \nu \overline{n_i} * \overline{H_i} + \varepsilon_{it}$$

where $\overline{n_i}$ is the average of the measure of multi-tasking (in 1992) for all jobs we observe for this individual in the dataset, and $\overline{H_i}$ is a vector with the average of the individual's schooling and experience levels while she was in the sample. If either are significant, then this implies that there is sorting on the basis of unobserved individual characteristics, and this might be responsible for the correlation between the level of multi-tasking and the returns to experience. The results for this second-stage are reported in Table 12. First, almost none of the effects are significant. Now since the second-stage regression includes an individual-level variable on the right hand side, and group 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 the ones reported, so the results will remain insignificant. The coefficient on teams is small and negative at the industry-level, though 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 was indeed a proxy for bad jobs and teams a proxy for good jobs. The coefficient of 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 fact that the effect of cross-training is positive. However, the coefficient of PSG and SPC are negative at the industry-level, and the effect of SPC is negative at the job-level as well. So it seems like there is limited evidence that there is positive selection into jobs with more new work practices (and that this can therefore explain why these jobs have higher returns to experience).

6 Conclusion

In this paper, I analyse whether the move towards new work practices involving multi-tasking may have changed the way in which wages grow over time for a particular worker. If more multi-tasking 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 multi-tasking. However, this may not be picked up right away if we only look at the returns to experience in the cross section. If both starting wages and wage growth are higher for jobs with more multi-tasking (and therefore for later cohorts of workers), then it may look like the cross-sectional returns to experience has actually gone down.

Using the PSID and data from an establishment-level survey conducted by Paul Osterman in 1992, I study the effects of multi-tasking on the returns to experience. I use the diffusion of various new work practices like teams and job rotation as proxies for multi-tasking, 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 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 5% when the percentage of firms using teams in the sector rises by 1. I also find that later cohorts choose jobs with a greater amount of multi-tasking, 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 multi-tasking, which implies that it is possible that jobs with more multi-tasking may have higher returns to experience because workers in jobs have higher unobserved ability.

Anecdotal evidence suggests that the increase in multi-tasking has been driven by changes in technology, particularly cheaper computing power. In

Autor et al. (2001) and Baker and Hubbard (2003), it is clear that it was the advent of computers that led to a change in the work organization. This paper then provides a previously overlooked link between technological change and the returns to experience, through the reorganization of jobs.

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