Return to Computer Use and Organizational Practices of the Firm

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Abstract

In this paper, we test the hypothesis that computer use will lead to productivity gains only if the firm uses an appropriate set of organizational practices. Detailed data on organizational practices and workers' compensation are obtained through a Canadian longitudinal linked employer-employee database called the Workplace and Employee Survey (WES). Linked data allow us to take into account both worker and firm unobserved heterogeneity through the estimation of a linear mixed model of wage determination. Our results suggest a small but positive computer-wage premium whose size is related to a set of organizational practices.

KEY WORDS: Wage determination; Human capital; New technologies; Computers; Mixed models; Linked employer-employee data; Organizational Practices of the Firm.

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1 Introduction

In this paper, we test whether or not the use of information technology (IT) at work leads to higher productivity. In the microeconomic literature, this has been tested using two methodologies. A first strand of the literature uses wage as a measure of worker productivity and examines the link between computer use and wage gain while controlling for worker selection. This literature finds negligible returns to computer use (DiNardo and Pischke (1997)). The second strand of the literature is based on production function estimation and links some measure of firm performance to investments in new technologies. This literature presents recent evidence that investments in information technology do lead to higher productivity. However, these productivity gains seem to depend on the firm's use of certain organizational practices such as team work or decentralization (Bresnahan, Brynjolfsson, and Hitt (2002)).

In order to reconcile these two sets of contradictory results, we use a new Canadian linked employer-employee data set (the Workplace and Employee Survey (WES)) containing information on both wages at the worker level and organizational practices at the firm level. While this allows us to explicitly control for organizational practices in our wage regression, we are also able to control for both unobserved heterogeneity at the worker and firm level because of the linked nature of the data. To do so, we use a mixed model of wage determination along the lines of Abowd and Kramarz (1999a).

It has long been recognized that controlling for unobserved worker heterogeneity is important if the set of workers using information technologies is self-selected based on unobserved factors like skills or unobserved human capital in general (DiNardo and Pischke (1997)). However, controlling for firm level unobserved heterogeneity might be even more important if firms differ in some unobserved way that affects both labour productivity and investments decisions in new technologies. This will be the case if (1) IT is a general-purpose technology that lowers the cost of some complementary innovations, (2) firms are heterogeneous in the cost reduction they face when implementing IT and (3) firms' investments in IT depend on this unobserved heterogeneity in cost reduction (Hitt and Brynjolfsson (2002), Bresnahan and Trajtenberg (1995)). Failure to take into account this unobserved firm heterogeneity will lead to biased estimates of the returns to computer use.

Our OLS and fixed worker effects results are similar to those found in the literature where the wage premium is estimated at 20% and 0%, respectively (see Krueger (1993) for similar OLS results and Entorf and Kramarz (1997) for similar results with individual fixed effects). However, once we control for unobserved firm heterogeneity in addition to worker heterogeneity, we find significant returns to computer use of 5-6%. This is different from Entorf, Gollac, and Kramarz (1999) who also control for firm unobserved heterogeneity through fixed effects and find no return to computer use[1]. Finally, we find evidence that returns to computer use are linked to organizational practices at the firm level in both fixed and mixed-effects specifications.

In the next section, we briefly review the two main approaches that have been used to link investment in new technologies and firm performance, focusing on empirical methodologies and results. We then turn to our statistical model, data description, results and conclusion.

2 Literature Review

We distinguish between two main approaches to estimate the impact of technology use on productivity at a microeconomic level. The first approach we

[1] These differences could be explained by higher computer returns in the late nineties or/and higher computer returns in North America as compared to Europe. Productivity growth differences in Europe and in the U.S. are documented in Gordon (2004).

discuss is based on wage regressions at the worker level while controlling for computer use (Krueger (1993), DiNardo and Pischke (1997) and Entorf and Kramarz (1997)[2]). We then turn to approaches based on production functions.

2.1 Results from Wage Regressions Estimation

In a widely cited study, Krueger (1993) estimates wage equations augmented for the use of a computer at work (C_i) by Ordinary Least Squares (OLS) using 1984 and 1989 U.S. microdata given by the Current Population Survey. More specifically, Krueger estimates:

$$\ln\ w_i = X_i\beta + \delta C_i + \epsilon_i \tag{1}$$

where X_i denotes a vector of demographic variables and where w_i denotes hourly wage. Krueger's specification includes a quadratic term in experience, years of education, race, marital status, gender as well as an interaction between gender and marital status. He also controls for union status, being a Vietnam veteran, working part-time and living in a metropolitan area. He finds that computer use on the job is related to a 15 to 20% wage premium (depending on the specification and on the year).

In a subsequent study, DiNardo and Pischke (1997) investigate the importance of selection in explaining the resultsl in Krueger (1993). More specifically, they question the assumption of exogenous computer use. Computer use is endogenous if firms are more likely to give computers to their most productive workers. If this is the case, Krueger's estimates of the computer-wage premium are likely to be biased. In DiNardo and Pischke (1997), the authors argue that the use of widely available "white collar" tools such as pencils, chairs, etc. at

[2] Recent examples include Chennells and Reenen (2002), Anger and Schwarze (2003), Lee and Kim (2004) and Dolton and Makepeace (2004).

work does not require any special ability and should not yield a premium to workers using them. Using German data, they find that workers who use these tools earn 9 to 14% more than nonusers who are otherwise identical based on observed characteristics[3]. They conclude that if there is an important selection effect in the use of pencils (which is what the return to the use of pencils suggests), then we should expect that selection is also important for the use of computers. If we assume the selection effect is responsible for 9-14% of the OLS wage premium, then return for computer use should fall to about 4-7%.

Entorf and Kramarz (1997) are, to our knowledge, the first to examine the computer wage premium using panel data to control for individual unobserved heterogeneity (ability) using person fixed effects[4]. Their database includes detailed information on the use of technology as well as on the characteristics of the workplace. They define three categories of technology. The first (NT_1) encompasses technologies that allow the user a higher degree of autonomy (e.g.: personal computers, word processors, etc.) The second (NT_2) includes technologies that allow the user average autonomy (for example, computer terminals for reception or emission only, etc.) The third (NT_3) includes technologies that leave little autonomy to the user (e.g.: robots, assembly chains, etc.) Given that the survey gives the date of the first use of the technology with the present employer, the authors are able to construct three variables that can proxy experience with each of the technological categories ($Exp(NTk)$).

The author estimate a version of equation (1) augmented with this additional information given by:

$$\ln\ w_{it} = \sum_{k=1}^{3} \alpha_k NTk_{it} + X_{it}\beta + \sum_{s=1}^{2}\sum_{k=1}^{3} \delta_{sk} Exp(NTk_{it})^s + u_i + \epsilon_{it} \qquad (2)$$

[3] Their data come from surveys performed in 1979, 1985-86 and 1991-92 by the Federal Institute for Vocational Training (BIBB) and the Institute for Labor Market Research (IAB).

[4] They use data from the «Enquêtes Emploi» (French Labor Force Surveys) of 1985-87 and from «Enquête sur la Technique et l'Organisation du Travail auprès des Travailleurs Occupés» (TOTTO) of 1987.

where w denotes monthly wage, X contains demographic information and firm characteristics and u denotes an employee fixed effect. With this specification, Entorf and Kramarz (1997) find that there is only a small return to experience with the technology of the first group (wage premia for the use of other types of technology are small and statistically insignificant). In a subsequent article, Entorf, Gollac, and Kramarz (1999) show that accounting for workplace unobserved heterogeneity simultaneously with worker unobserved heterogeneity (as Abowd, Kramarz, and Margolis (1999)) does not change their earlier conclusion.

2.2 Results from Production Function Estimation

The consensus in the computer-wage-premium literature appears to be that apart from a small return to experience with the technology, there is no significant return to the use of a computer (see for example chapter 6 in Levy and Murname (2004)). However, some recent results from production function estimation seem to contradict these findings. This second approach uses firm (or industry) level data to estimate production functions, generally within the manufacturing sector (see especially Bartel and Sicherman (1999), Berman, Bound, and Griliches (1994), Doms, Dunne, and Trostke (1997) and Autor, Katz, and Krueger (1998)). The focus of this literature (while initially about the relationship between the use of new technologies, productivity gains and relative demand for qualified workers) has recently moved to incorporate the additional impact of the firm's organizational practices (Brynjolfsson and Hitt (1995), Bertschek and Kaiser (2001), Black and Lynch (2001), Bresnahan, Brynjolfsson, and Hitt (2002), Hitt and Brynjolfsson (2002) and Brynjolfsson and Hitt (2003)).

Brynjolfsson and Hitt (1995) use firm fixed effects to control for the endogeneity of information technology (IT) investments in the estimation of production functions. Their estimates show that in the U.S., from 1988 to 1992, controlling for firm unobserved heterogeneity explains as much as 50% of the productivity gains from IT investments as compared to OLS estimates, while leaving other coefficients almost unaffected. They conclude that unobserved organizational practices of the firm probably affect the return to investments in IT.

In another attempt to control for endognous IT investments, Bertschek and Kaiser (2001) estimate a simultaneous equation model for the impact of IT investments and work reorganizations on German firm productivity in 2000. Firms are assumed to undergo some kind of work reorganization if the benefits of the reorganization outweight the associated costs. They find that elasticities of IT and non-IT investments are not statistically different between firms that reorganized and those that did not. However, the point estimates are generally larger with reorganization than without. Using kernel density technique, they show that the entire distribution shifts to the right suggesting a positive relation between workplace reorganization and labor productivity.

Similar results are obtain by Brynjolfsson and Hitt (2003). They examine the relationship between growth in computer investments and growth in output in the U.S. between 1987 to 1994. They find a positive relationship between the impact of lagged computer investments on output growth, the cumulative impact being stronger when earlier investments are added to the specification. Their interpretation is that short term returns are a measure of the direct effect of IT investments while longer returns give information on a combined return of both IT and organizational investments.

Some noteworthy results also come from Bresnahan, Brynjolfsson, and Hitt (2002) who make the hypothesis that skill-biased technological change is the result of a mixture of complementary changes that comprise IT and organizational practices[5]. In a cross-sectional setting, they find that firms choosing high IT and low organizational practices (WO)[6] (or the opposite) or low IT and low WO have lower productivity gains than firms that choose high IT and high WO. They also find complementarity between the level of human capital (HK) and WO as well as between HK and IT[7].

The basic idea behind the analysis in Bresnahan, Brynjolfsson, and Hitt (2002) is that IT investment does not relate to traditional capital investment but rather to general-purpose technology (Hitt and Brynjolfsson (2002)). General-purpose technology can be defined as technology that induces cost reductions in other innovations. A well-known example of such a technology is the telegraph. As telegrams became widely available, geographically disperse firms became more viable (hence a technological innovation induced a cost reduction in an organizational innovation[8]).

From this discussion, one can conclude that there appears to be a consensus in this literature about the positive relationship between the use of technology, the use of organizational practices and firm productivity. Nonetheless, there is still disagreement as to the size of the effects. These results outline a gap between wage regression results and those from production function estimations. In the next section, we show how the organizational practices of the firm and both unobserved worker and firm heterogeneity can be taken into account in a model of wage determination.

[5] The skill biased technological change hypothesis explains the growing wage inequalities by complementarity between IT and qualified work (see, for instance, Bound and Johnson (1992) and Card and DiNardo (2002)).

[6] Their measure of WO is an index that reflects different measures of workplace organization: greater use of teams, greater delegation, etc.

[7] See also Black and Lynch (2001) and Hitt and Brynjolfsson (2002).

[8] See Milgrom and Roberts (1992).

3 Statistical Model

To model wage determination, we use a two-factor analysis of covariance with repeated observations along the lines of Abowd and Kramarz (1999b):

$$y_{it} = \mu + \mathbf{x}_{it}\boldsymbol{\beta} + \theta_i + \psi_{j(i,t)} + \epsilon_{it} \tag{3}$$

with

$$\theta_i = \alpha_i + \mathbf{u}_i\boldsymbol{\eta} \tag{4}$$

where y_{it} is the (log) wage rate observed for individual $i = 1, ..., N$, at time $t = 1, ..., T_i$. Person effects are identified by i, firm effects by j as a function of i and t, and time effects by t. μ is a constant, $\mathbf{x}_{it}$ is a matrix containing demographic information for employee i at time t as well as information concerning the workplace j to which the worker i is linked. Although β and η can be fixed or random, we assume they are fixed in our estimations. All other effects are random. Personal heterogeneity (θ_i) is a measure of unobserved (α_i) and observed $(\mathbf{u}_i\boldsymbol{\eta})$ human capital and follows the worker from firm to firm. Employer heterogeneity $\left(\psi_j\right)$ is a measure of firm-specific compensation policies and is paid to all workers of the same firm[9]. ϵ_{it} is the statistical residual.

Estimation of (3) on large-scale data sets has been achieved by Abowd, Kramarz, and Margolis (1999) while treating firm and person effects as fixed. Our focus on a mixed-model specification for wage determination is done without loss of generality since it can be shown that the least squares estimates of the fixed effects are a special case of the mixed model estimates (see Abowd and Kramarz (1999a)).

[9] Firm unobserved heterogeneity in productivity is a common factor in many models of wage dispersion, see Mortensen (2003).

In full matrix notation, we have

$$y = X\beta + U\eta + D\alpha \; + F\psi + \epsilon \tag{5}$$

where : y is the $N^* \times 1$ vector of earnings outcomes; X is the $N^* \times q$ matrix of observable time-varying characteristics including the intercept; β is a $q \times 1$ parameter vector; U is the $N^* \times p$ matrix of time invariant person characteristics; η is a $p \times 1$ parameter vector; D is the $N^* \times N$ design matrix of the unobserved component for the person effect; α is the $N \times 1$ vector of person effects; F is the $N^* \times J$ design matrix of the firm effects; ψ is the $J \times 1$ vector of pure firm effects; and ϵ is the $N^* \times 1$ vector of residuals.

Finally, we assume α and ψ to be distributed normally :

$$\begin{bmatrix} \alpha \\ \psi \\ \epsilon \end{bmatrix} \tilde{} \; N\left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_\alpha^2 I_N & 0 & 0 \\ 0 & \sigma_\psi^2 I_J & 0 \\ 0 & 0 & \Lambda \end{bmatrix} \right) \tag{6}$$

where

$$\Lambda = \begin{bmatrix} \Sigma_1 & 0 & ... & & 0 \\ ... & ... & & & ... \\ 0 & ... & \Sigma_i & ... & 0 \\ ... & & & ... & ... \\ 0 & & ... & 0 & \Sigma_N \end{bmatrix}$$

and

$$\Sigma_i = V\left(\epsilon_i\right)$$

4 Estimation

Parameters estimates are obtained in two steps. We first use Restricted Maximum Likelihood (REML) methods to get parameter estimates for the variance components in (6). We then solve the mixed equations to get estimates for the other parameters in the full model (5). We discuss each of these steps in turn.

REML methods involve applying maximum likelihood (ML) to linear functions of y, i.e. $K'y$ (McCulloch and Searle (2001)). Note that K' is specifically designed so that $K'y$ contains none of the fixed effects (β and η in our case) which are part of the model for y. Thus, REML is simply ML applied on $K'y$ and can be interpreted as maximizing a marginal likelihood.

Each vector of K is chosen so that $k'y = 0$ or $K'[X \quad U] = 0$. With $y \sim N(X\beta + U\eta, V)$ it follows that

$$K'y \sim N(0, K'VK)$$

where $V = DD'\sigma_\alpha^2 + FF'\sigma_\psi^2 + \Lambda$ is the covariance of earnings implied by (6). The REML log-likelihood is therefore

$$\log L_{REML} = -\frac{1}{2}(N^* - r)\log 2\pi - \frac{1}{2}\log|K'VK| - \frac{1}{2}y'K(K'VK)^{-1}K'y \quad (7)$$

There are two advantages of using REML. First, variance components are estimated without being affected by the fixed effects. This means that the variance estimates are invariant to the values of the fixed effects. Second, in estimating variance components with REML, degrees of freedom for the fixed effects are taken into account implicitly whereas with ML they are not[10]. Both methods have the same merits of being based on the maximum likelihood principle and

[10] REML estimates are also invariant to whatever set of contrasts is chosen for $K'y$ as long as K' is of full rank (Searle, Casella, and McCulloch (1992)).

parameter estimates inherit the consistency, efficiency, asymptotic normality and invariance properties that follow.

Maximization of the likelihood function (7), while providing us with estimates for the variance components in (6), will not yield estimates for the random and fixed effects. In a second step, we obtain estimates for the random and fixed effects using a set of equations developed by Henderson, Kempthorne, Searle, and Krosigk (1959). These equations have become known as Henderson's Mixed Model Equations (MME) and simultaneously yield the Best Linear Unbiased Estimates (BLUE) of the fixed effects and Best Linear Unbiased Predictors (BLUP) of the random effects for known values of the variance components and Λ[11]. Define the matrix of variance components as

$$\Omega = \begin{bmatrix} \sigma_\alpha^2 I_N & 0 \\ 0 & \sigma_\psi^2 I_J \end{bmatrix}. \tag{8}$$

For the particular structure implied by (5) and (6) , the MME are

$$\begin{bmatrix} \begin{bmatrix} X' \\ U' \end{bmatrix} \Lambda^{-1} [X \;\; U] & \begin{bmatrix} X' \\ U' \end{bmatrix} \Lambda^{-1} [D \;\; F] \\ \begin{bmatrix} D' \\ F' \end{bmatrix} \Lambda^{-1} [X \;\; U] & \begin{bmatrix} D' \\ F' \end{bmatrix} \Lambda^{-1} [D \;\; F] + \Omega^{-1} \end{bmatrix} \begin{bmatrix} \hat{\beta} \\ \hat{\eta} \\ \hat{\alpha} \\ \hat{\psi} \end{bmatrix} = $$

$$= \begin{bmatrix} \begin{bmatrix} X' \\ U' \end{bmatrix} \Lambda^{-1} y \\ \begin{bmatrix} D' \\ F' \end{bmatrix} \Lambda^{-1} y \end{bmatrix}. \tag{9}$$

Estimates for Λ and Ω are obtained from the REML step.

[11]BLUE and BLUP estimates make us feel quite confident that a full information approach would not yield any better (in the sense of lower variance) estimator, although it might if we were to use a different class of estimators.

Two important points should be made about the estimates for $\left(\hat{\beta}, \hat{\eta}, \hat{\alpha}, \hat{\psi}\right)$. First, mixed model solutions $\left(\hat{\beta}, \hat{\eta}, \hat{\alpha}, \hat{\psi}\right)$ converge to the least squares solutions as $|\Omega| \to \infty$ (if $\Lambda = \sigma_\epsilon^2 I_{N^*}$). In this sense, the least squares solutions are a special case of the mixed model solutions. Second, unlike the usual random effects specification considered in the econometric literature, (5) and (6) do not assume that the random effects are orthogonal to the design (X and U) of the fixed effects (β and η), that is we do not assume $X'D = X'F = U'D = U'F = 0$. If this were the case, we could solve for $\hat{\beta}$ and $\hat{\eta}$ independently of $\hat{\alpha}$ and $\hat{\psi}$.

4.1 Identification

Identification of individual and firm random effects comes from the longitudinal and linked aspects of the data as well as from distributional assumptions. For individual effects, identification comes from the repeated observations on each individual over time. Identification of firm effects comes from repeated observations on workers from the same firm. Note that it would not be possible in our settings to identify firm and individual fixed-effects since we do not observe workers moving from firm to firm. When this is the case, parametric assumptions embedded in the mixed model are necessary to distinguish firm and individual unobserved heterogeneity. Note that this also precludes the inclusion of worker-firm match effects.

5 Data

We use data from the 1999 and 2000 versions of the Workplace and Employee Survey (WES) conducted by Statistics Canada[12]. The survey is both longitudinal and linked in that it documents the characteristics of the workers and of the

[12] This is a restricted-access data set available in Statistics Canada Research Data Centers (RDC).

workplaces over time[13]. The target population for the "*workplace*" component of the survey is defined as the collection of all Canadian establishments who paid employees in March of the year of the survey. The sample comes from the "Business registry" of Statistics Canada which contains information on every business operating in Canada. The survey, however, does not cover the Yukon, the Northwest Territories and Nunavut. Firms operating in fisheries, agriculture and cattle farming are also excluded.

For the "*employee*" component, the target population is the collection of all employees working, or on paid leave, in the workplace target population. Employees are sampled from an employees list provided by the selected workplaces. For every workplace, a maximum number of 12 employees is selected and for establishments with less than 4 employees, all employees are sampled. In the case of total non-response, respondents are withdrawn entirely from the survey and sampling weights are recalculated in order to preserve representativeness of the sample. WES selects new employees and workplaces in odd years (at every third year for employees and at every fifth year for workplaces). Hence, the survey can only be representative of the whole target population during these re-sampling years.

We restrict our sample to employees who had the same employer in 2000 that they had in 1999 and to those who have non-missing answers for our variables of interests. For the 1999 version of the survey, there are 23 540 employee respondents. Of this number, 18 267 still had the same employer and responded in 2000. For workplaces, 5733 responded in 1999 and 5 320 in 2000[14].

To consider the effect of organizational design on pay, we restrict our sample

[13] Abowd and Kramarz (1999b) classify WES as a survey in which both the sample of workplaces and the sample of workers are cross-sectionally representative of the target population.

[14] For 1999, we deleted the 586 non-responses from workplaces. We also removed a total of 745 workplaces in 2000 (these are the workplaces associated with the 2512 employees that were deleted from the 2000 sample.) The 2000 version of WES contains information on 20 779 employees. From this number, 2512 correspond to workers who stop being employed by a workplace in the sample or to workers linked to a workplace that did not respond in 2000.

further. This is necessary, as the questions on work practices are intended only for establishments with more than 10 employees and because there are some non-responses to these questions. The final sample size is then 19 098 employees with 3771 workplaces in 1999 and 15 048 employees and 3647 workplaces in 2000. Estimation results below are shown for the full sample and the sub-sample with information on organizational practices. Note that to control for the design effect in our estimations, we weighted our analyses with the final sampling weights for employees as recommended by Statistics Canada.

5.1 Variables Used

A complete list of variables used and descriptions is provided in Table 1. Our measure of computer use at work (CPU) excludes cash registers, sales terminals, scanners, manual typewriters and industrial vehicles or machines which are classified as "other technological devices (othtech)". Computer-controlled or computer-assisted technology like industrial robots, retail scanning systems, etc. are covered by variable CAT. We also have information on lifetime experience with a computer in a work environment (exp_cpu).

For the workplace's organizational practices, we have information on the use of various practices for non-managerial employees and for organizational changes during the years of the survey. While information on organizational change was collected in both years, information on organizational practices was collected only in 1999. Since a firm is likely to use more than one practice, we aggregate organizational practice variables into six groups according to the level of correlation between them[15]. The creation of the six groups is summarized in Table 2. Our first group (OP1) comprises: greater integration among functional areas, increase in the degree of centralization and re-engineering. A second group (OP2) is composed of: increase in the degree of decentralization,

[15]Estimation results with dissagregated organizational practices are available upon request.

reduction in the number of managerial levels, downsizing, adoption of flexible working hours, greater reliance on job rotation and implementation of total quality management. The third group (OP3) encompasses: greater reliance on external suppliers, greater inter-firm collaboration in R&D and production, increase in the use of temporary workers, increase in the use of part-time workers and increase in the use of overtime hours. A fourth group (OP4) is composed of: use of employee suggestion, information sharing with employees and use of flexible job design. The fifth group (OP5) encompasses: use of problem solving teams, use of self-directed groups and the use of joint labor-management committee. Finally, the last group (OP6) contains all other organizational changes.

5.2 Descriptive Statistics

Table 3 shows the probability of computer use at work for various demographic categories for both 1999 and 2000. For 1999 (2000), approximately 60% (65%) of the Canadian workforce used a computer at work, an increase of 5% on a year-by-year basis. Note that among all employees in our sample, 58.5% were computer users in both years, 33.8% were non-users in both years, 2.7% used the computer only in 1999 and 5.0% used it only in 2000. Being female, not part of an union, and having a higher level of education are associated with higher computer usage. Among occupations, managers, clerks and professionals seem more likely to use a computer. Finally, workers in the "finance and insurance", "business services" or "information and cultural" sectors are also more likely to use a computer at work than those in other sectors. These patterns are similar to those provided by Autor, Katz, and Krueger (1998) for the U.S. and by DiNardo and Pischke (1997) for Germany[16]. Their summary statistics show that the probability of using a computer at work rises with the level of education both in the U.S. and in Germany. U.S. statistics suggest that female workers

[16] See Table 1 in DiNardo and Pischke (1997).

were more likely than male workers to use the computer while for Germany there is no clear difference between female and male workers.

Table 4 and 5 present descriptive statistics for all variables used in our analysis. It is not possible for confidentiality reasons to show minima and maxima. It shows that average education in the sample is slightly higher than "some college education", that 52.5% of the employees are members of a union, that 42.1% are females and that 56.5% are married. Around 43% of the employees are technician and almost 19% are professional while 16% are clerical workers. The most represented sectors are "labour-intensive tertiary" and "education and health services" with 24.1% and 21.5% respectively. 55% of the workplaces in the sample use at least one organizational practices from group 1 mainly due to the fact that 45.7% (27%) of the workplaces reported undergoing some form of reengineering (integration). The same is true for practices of the second group with 20% of the workplaces using job rotation. The most common set of organizational practices is group 4 with 67.8% of the workplaces reported using employee's suggestion, flexible job design or information sharing with employees. Finally, only 2.7% of the workplaces reported using some other form of organizational change (OP6).

6 Results

Our main results are presented in Tables 6 to 8. Table 6 presents estimates a methodology and a set of explanatory variables similar to Krueger (1993). Columns 1 and 3 show Weighted Least Squares (WLS) estimates for a specification without a dummy for the use of a computer for 1999 and 2000, respectively, while we incorporate the impact of computer use in columns 2 and 4. Table 7 presents estimated coefficients for a specification that includes experience with the computer, use of CAT or other technologies, seniority and firm size for pooled OLS (column 1), individual fixed effects (column 2) and mixed effects (column 3). Note that for the results in columns (1) and (2), our specification and methodology are similar to Entorf and Kramarz (1997) while column (3) shows coefficients obtained through our mixed model specification. Also, all regressions in Table 7 now include both industry[17] and occupation[18] dummies. Finally, Table 8 presents (pooled OLS, individual fixed effects and mixed effects) estimates for specifications from Table 7 augmented with controls for organizational practices that are also interacted with computer use indicators. We check the robustness of our results in Tables 9 and 10. Table 9 shows the impact of including occupation and industry dummies on the estimated return to computer use. Table 10 presents coefficient estimates on the whole sample, i.e. including firms that were not asked about organizational practices.

6.1 Returns to Computer Use

From Table 6, we see that the cross-sectional computer wage premium is significant at around 21.6% and 21.9% in 1999 and 2000 respectively. If we include dummies for occupation (results not shown), returns to computer use drop slightly to about 18%. These results are also very much in line with Krueger (1993) estimates (15 to 20%). Focusing on column (4), we see that returns to education and experience are also significant at about 5% and 3% respectively. Surprisingly, being part of a union is associated with a wage gain of 14.2%. In fact, taking into account computer use makes the return to being part of a union increase by about 3.6%[19]. Note that neither race nor working part-time have a significant impact on wages but being male and being married has a significant

[17] Natural resources, labour tertiary, primary manufacturing, secondary manufacturing, capital tertiary, construction, transport, communication, retail, finance and insurance, real estate, business services, education and health care and information and culture.

[18] Manager, professional, technician/trades, sales/marketing, clerical/administrative and production without certificate.

[19] Union-nonunion wage differentials in WES are examined in details in Verma and Fang (2004).

positive impact on wages. While these results are presented for comparison purposes with Krueger (1993), caution should be applied in the interpretation since we do not control for firm characteristics, occupations, unobserved human capital and unobserved firm heterogeneity.

6.2 Controlling for Unobserved Ability

Table 7 compares three specifications that include a similar set of explanatory variables as those used by Entorf and Kramarz (1997) and Entorf, Gollac, and Kramarz (1999). More specifically, we now include years of experience with a computer in a work environment, seniority, CAT use indicators as well as an indicator for the use of other technologies, industry and occupation dummies and controls for firm size. We compare pooled OLS results in column (1) to fixed individual effects (to control for unobserved ability) in column (2) and mixed effects (to control for firm unobserved heterogeneity) in column (3).

We find in column (1) that computer use is now associated with a wage premium of 10% while using CAT brings no wage gains. However, using other technologies generates a statistically significant negative return. Also, returns to computer experience are close to 1.3% per year. It is normal to find a lower return to computer use when controlling for computer experience.

In column (2), we find that taking into account individual unobserved ability brings the return to computer use to zero. Again, these results are similar to those obtained by Entorf and Kramarz (1997) who also controlled for unobserved human capital through fixed effects. Note that taking into account unobserved individual heterogeneity also lowers returns to schooling and seniority while returns to experience stay at around 1% per year. The firm-size wage premium also drops down for average and large size firms, consistent with the hypothesis that bigger firms employ more able worker. In general, coefficient estimates are somewhat imprecise in the fixed effects specification as can be seen by the size of the standard errors. This would presumably improve with a longer panel.

Column (3) shows estimates for the mixed-effects model of wage determination where we take into account both unobserved worker and workplace heterogeneity. Returns to computer use are about half what they were in the pooled OLS case but much higher than in the fixed effect specification. This seems to indicate that failure to take into account workplace unobserved heterogeneity will lead to biased estimates on the returns to computer use for reasons explained above. In fact, we do a likelihood ratio test of no firm unobserved heterogeneity and reject the null hypothesis quite strongly. The return to computer use experience also fell to 1%. Using CAT is not associated with a significant wage premium, but using other technologies is still associated with a significant and negative return[20].

These last results are different from Entorf, Gollac, and Kramarz (1999) in that we find evidence of a positive and statistically significant computer wage premium with methodologies controlling for both unobserved heterogeneity at the firm and worker level. These differences could be explained by higher computer returns in the late nineties or/and higher computer returns in North America as compared to Europe.

6.3 Controlling for Organizational Practices

Table 8 again shows estimates of pooled OLS, fixed- and mixed-effects models of wage determination that now include explicit controls for the organizational practices of the firm. Note that these practices appear both in levels and in interaction with computer use dummies. We only discuss our preferred specification that takes into account both worker and workplace unobserved heterogeneity in

[20] Remember that "other technologies" include mostly machines or technological devices that demand relatively low skill levels from labor, like cash registers and sales terminals scanners.

column (3).

Once again, we find a statistically significant wage premium for the use of a computer (close to 8.8%). Note that this return is not dependent on the use of a particular organizational practice. Because of the interactions, we also compute the marginal effect (at the mean of the observable variables). The wage increase associated with the use of a computer is then of 6.4%. This is a slightly higher figure than for the specification without practice and interaction dummies. Note that we still find statistically significant returns to computer experience with the computer (0.9%).

Turning to the impact of the organizational practices on wages, we find a statistically significant positive impact for workplaces that implemented some changes included in our "OP2" (1.1%), "OP4" (3.3%), "OP5" (3.4%) and "OP6" (3.6%) indices. Negative wage premia are found for "OP1" and "OP3" which both involves significant restructuration of the firm. When interacted with computer use, only our "OP1", "OP3" and "OP6" indices yields positive wage premia while "OP2", "OP4" and "OP5" have a negative effect on wages. In the terminology of Bresnahan, Brynjolfsson, and Hitt (2002), this would mean that organizational practices from "OP1", "OP3" and "OP6" are complementary to computer use while other practices would act as substitutes for productivity improvements purposes[21].

[21] Other explanations have been provided to explain the negative (positive) interactions between organizational practices and computer use. First, it might be that working in a firm that has implemented these organizational practices in conjunction with using the computer yields a lower (higher) disutility of labor thus enabling the firm to entice the worker to accept a lower (higher) wage. Second, it could be that using the computer in conjunction with the firm making use of a particular organizational practice renders the work of the individual easier (harder) to control by the employer, thus lowering (augmenting) the need for incentive pay.

6.4 Robustness Checks

Table 9 provides some specification checks for the Pooled OLS and mixed models. Columns (1) and (3) of Table 9 should be compared to columns (1) and (3) of Table 7 to show the impact of the inclusion of industry and occupation dummies. It can be seen that returns to computer use increase by about 3% when these controls are included. Returns to seniority, experience and schooling also increase somewhat. Columns (2) and (4) are to be contrasted with columns (1) and (3) of Table 8. When not interacted with computer use, most organizational practices bring positive (but small) wage gains except in the case of "OP6" where wage gains are considerably higher at 4.4%.

In Table 10, we look at the impact of computer use of the full sample (remember that we restricted our sample earlier to the set of firms that were asked about their organizational practices (minimum 10 employees). Bringing back the smaller firms lowers the returns to computer use to about 3.9%.

7 Conclusion

This paper presents a careful analysis of whether there exists a computer wage premium in Canada in 1999 and 2000 and whether this premium is related to the organizational practices of the firm, something that has never been done before. Our estimates suggest that a worker who uses the computer at work earns between 5-6% more than a nonuser. This results is robust to the use of a methodology that allows us to control for both firm unobserved heterogeneity and employee unobserved human capital.

Our results also suggest that for some particular organizational practices, there is a positive relationship between the implementation of these practices by the workplace and the use of the computer. Furthermore, our mixed-effect methodology shows that there is a significant (both numerically and statistically) wage premium for computer use conditional on the use of no particular organizational practices. This suggests that wage gains from computer use can be higher if the "correct" choice of practices is made, but that these practices do not determine the existence of the computer-wage premium altogether. It reflects the fact that the work environment is modified as a result of the introduction of the technology and that workplace organization has to adapt to this new reality. It is also consistent with the macroeconomic literature that suggests that the lag between the investment in technology and the appearance of the aggregate productivity gains is attributable to learning by doing.

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Table 1: Variables description

Dependent variable	
Wage	Natural logarithm of the converted hourly wage.
Year	1: for data from the 2000 version of the survey.
Demographic characteristics	
Female	1: female.
Married	1: married.
Black	1: has black parents or grandparents.
Othraces	1: has neither black nor white parents or grandparents
Education	Years of education
Experience	Number of years of work experience.
Job characteristics	
Seniority	Seniority in years.
Union	1: covered by a collective bargaining agreement
Ptime	1: works usually less than 30 hours per week.
Use of technology	
CPU	1: if uses the computer at work.
CAT	1: if computer-controlled technology
Othtech	1: if employee uses other machine or technological device
Exp_cpu	Years of lifetime experience with a computer.
Number of employees	
Very small	1: between 1 and 19 employees.
Small	1: 20 and 99 employees.
Average	1: 100 and 499 employees.
Large	1: 500 or more employees.

Table 2: Workplace Organizational Practices

OP1	1: if changes in	integration centralization re-engineering
OP2	1: if experiences	increase in decentralization reduction in the number of managerial level downsizing implementation of total quality management greater reliance on job rotation and multiskilling adoption of flexible working hours
OP3	1: if greater reliance on	firm inter-collaboration in R&D and production external suppliers of products and services part-time workers overtime hours temporary workers
OP4	1: if uses	employees' suggestions flexible job design information sharing with employees
OP5	1: if uses	problem solving teams self-directed groups joint labour-management committee
OP6	1: if experienced change in organisation of some other form	

Table 3: Computer usage

Groups	1999	2000
All workers	60.1	65.2
Men	57.9	61.8
Women	63.5	68.3
White	60.9	65.2
Black	54.8	63.5
Other	60.7	65.1
Union status		
Union member	51.5	55.3
Nonunion	64.4	69.4
Schooling		
Less than high school	34.0	39.7
High school	52.1	56.4
Some college	65.0	67.6
College	66.5	71.0
Post college	83.7	85.4
Occupations		
Manager	81.9	88.4
Professional	84.7	87.7
Technician/trades	46.3	50.6
Marketing/sales	41.2	46.4
Clerical/administrative	84.8	87.3
Production without certificate	18.3	20.0
Industries		
Forestry, mining, oil, and gas extraction	54.9	54.9
Primary product manufacturing	49.6	53.3
Secondary product manufacturing	56.4	59.1
Labour intensive tertiary manufacturing	40.0	45.4
Capital intensive tertiary manufacturing	67.6	67.3
Construction	37.6	34.8
Transportation, warehousing, wholesale	65.5	67.2
Communication and other utilities	66.8	69.9
Retail trade and consumer services	47.2	54.7
Finances and insurance	93.9	94.6
Real estate, rental and leasing operations	65.9	69.2
Education and health services	63.5	66.5
Information and cultural industries	86.1	88.9
Business services	79.6	85.1
Experience		
[0-10) years	61.7	66.6
[10-20) years	58.4	61.5
[20-30) years	55.9	61.2
[30 years and more	59.0	55.6
Number of observations	23540	18267

Table 4: Descriptive statistics

	Mean	Std Dev.	5%	50%	95%
Wage	2.898	0.465	1.960	2.803	3.634
Education	16.017	3.571	10.000	16.000	22.000
Experience	19.148	10.285	1.000	16.000	35.000
Experience ^2 / 100	4.724	4.284	0.010	2.560	12.250
Seniority	8.523	7.573	0.917	4.417	22.000
Seniority ^2 /100	1.300	2.171	0.008	0.195	4.840
Exp_cpu	6.651	6.776	0.000	5.000	20.000
Exp_cpu ^2 /100	0.901	1.431	0.000	0.250	4.000
CPU	0.627	0.483	0.000	1.000	1.000
_N = 41807					

Table 5: Descriptive statistics (Indicators)

	Mean	Std Dev.
Union	0.525	0.499
Year	0.480	0.500
Black	0.008	0.088
Othraces	0.221	0.415
Ptime	0.029	0.168
Female	0.421	0.494
Married	0.565	0.496
Married*Female	0.215	0.411
CAT	0.162	0.368
Othtechs	0.224	0.417
Occupations		
Manager	0.094	0.292
Professional	0.188	0.391
Technician	0.434	0.496
Marketing/sales	0.041	0.199
Clerical/administrative	0.163	0.370
Production without certificate	0.080	0.271
Natural ressources	0.012	0.110
Labour tertiary	0.241	0.428
Primary manufacturing	0.039	0.194
Secondary manufacturing	0.029	0.168
Capital tertiary	0.050	0.217
Industry		
Construction	0.024	0.152
Transport	0.135	0.342
Communication	0.015	0.123
Retail	0.126	0.331
Finance and insurance	0.031	0.174
Real estate	0.009	0.094
Business services	0.050	0.217
Education and health services	0.215	0.411
Culture and information	0.024	0.153
Workplace size		
Small	0.248	0.432
Average	0.281	0.281
Large	0.284	0.451

Table 5: Con't

	Mean	Std Dev.
Organizational practices		
Suggestion	0.310	0.463
Flexible ind.	0.243	0.429
Info. Sharing	0.519	0.500
Problems solving	0.332	0.471
Comitee	0.380	0.485
Self-directed groups	0.153	0.360
Organizational changes		
Integration	0.270	0.444
Hierarchy	0.124	0.330
Rotation	0.240	0.427
TQM	0.156	0.363
External	0.148	0.355
Collaboration	0.121	0.326
Other changes	0.019	0.135
Centralization	0.146	0.353
Downsizing	0.134	0.340
Decentralization	0.127	0.333
Temporary	0.092	0.289
Part-time change	0.130	0.336
Re-engineering	0.457	0.498
Overtime	0.202	0.402
Flexible	0.100	0.301
OP Indices		
OP1	0.553	0.497
OP2	0.550	0.498
OP3	0.481	0.500
OP4	0.678	0.467
OP5	0.584	0.493
OP6	0.027	0.162

Table 6: Impact of Computer Use in Basic Linear Models

	1999		2000	
	(1)	(2)	(3)	(4)
Intercept	1.614***	1.666***	1.510***	1.544***
	(0.032)	(0.032)	(0.036)	(0.037)
CPU		0.216***		0.219***
		(0.015)		(0.017)
Union	0.153***	0.183***	0.109***	0.142***
	(0.014)	(0.014)	(0.014)	(0.014)
Education	0.052***	0.042***	0.059***	0.050***
	(0.002)	(0.002)	(0.002)	(0.002)
Exp.	0.029***	0.025***	0.037***	0.033***
	(0.002)	(0.002)	(0.002)	(0.002)
Exp. ^2 / 100	-0.046***	-0.038***	-0.062***	-0.054***
	(0.006)	(0.006)	(0.006)	(0.005)
Black	-0.063	-0.049	-0.093	-0.090
	(0.077)	(0.068)	(0.077)	(0.066)
Othraces	-0.027**	-0.022	-0.021	-0.015
	(0.014)	(0.014)	(0.015)	(0.014)
Ptime	-0.076***	-0.034	-0.098**	-0.047
	(0.028)	(0.028)	(0.039)	(0.041)
Female	-0.162***	-0.176***	-0.179***	-0.188***
	(0.020)	(0.020)	(0.022)	(0.023)
Married	0.163***	0.157***	0.143***	0.144***
	(0.020)	(0.019)	(0.022)	(0.022)
Married*Female	-0.044*	-0.042**	-0.056**	-0.064
	(0.026)	(0.026)	(0.028)	(0.028)
R-squared	0.318	0.353	0.350	0.384
Sample size	23540	23540	18267	18267

Statistical significance: *=10%; **=5%; ***=1%
Robust standard errors in parentheses.

Table 7: Impact of Computer Use in OLS, Fixed- and Mixed-Effects Models

	Pooled OLS (1)	Fixed effect (2)	Mixed effects (3)
Year	0.023**	-0.046	0.019***
	(0.009)	(0.060)	(0.002)
Intercept	1.876***	1.402	2.017***
	(0.042)	(1.085)	(0.025)
CPU	0.095***	-0.002	0.047***
	(0.042)	(0.040)	(0.006)
CAT	0.026***	-0.004	-0.011
	(0.013)	(0.017)	(0.005)
Othtech	-0.033***	-0.067	-0.013***
	(0.011)	(0.015)	(0.004)
Exp_cpu	0.013***	0.002	0.010***
	(0.002)	(0.005)	(0.001)
Exp_cpu ^2/100	-0.026***	-0.000	-0.018***
	(0.010)	(0.019)	(0.004)
Education	0.022***	0.004	0.024***
	(0.001)	(0.011)	(0.002)
Exp.	0.015***	0.090	0.015***
	(0.002)	(0.066)	(0.001)
Exp. ^2/100	-0.024***	-0.016	-0.024***
	(0.005)	(0.039)	(0.002)
Seniority	0.007***	-0.010**	0.000
	(0.002)	(0.005)	(0.001)
Seniority ^2/100	-0.009**	0.012	0.005
	(0.006)	(0.030)	(0.003)
Black	-0.029		-0.052*
	(0.043)		(0.027)
Othraces	-0.022		-0.020***
	(0.009)		(0.006)

Table 7: Cont'd

	Pooled OLS	Fixed effect	Mixed effects
	(1)	(2)	(3)
Female	-0.101***		-0.106***
	(0.016)		(0.008)
Married	0.093***	0.039	0.072***
	(0.013)	(0.038)	(0.006)
Married*Female	-0.038**	-0.028	-0.037***
	(0.018)	(0.056)	(0.009)
Part-time	0.029	-0.033	-0.031***
	(0.023)	(0.048)	(0.009)
Union	0.067***	0.163**	0.081***
	(0.011)	(0.081)	(0.006)
Small size	0.045***	0.045**	0.054***
	(0.017)	(0.022)	(0.008)
Average size	0.149***	0.079***	0.118***
	(0.017)	(0.026)	(0.010)
Large size	0.206***	0.110***	0.184***
	(0.018)	(0.029)	(0.118)
Occupation dummies	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes
R-squared	0.525		
Sample size	34146	34146	34146

Statistical significance: *=10%; **=5%; ***=1%.
Robust standard errors in parentheses.

Table 8: Organizational Practices and Returns to Computer Use

	Pooled OLS	Fixed effect	Mixed effects
	(1)	(2)	(3)
Year	0.022**	-0.046	0.018***
	(0.009)	(0.058)	(0.002)
Intercept	1.844***	1.448	1.979***
	(0.044)	(1.060)	(0.026)
CPU	0.112***	0.067	0.088***
	(0.025)	(0.043)	(0.010)
CAT	0.023*	-0.003	-0.001
	(0.013)	(0.016)	(0.005)
Other technologies	-0.032***	-0.006	-0.012***
	(0.011)	(0.015)	(0.004)
Exp_cpu	0.012***	0.002	0.009***
	(0.002)	(0.005)	(0.001)
Exp_cpu ^2 /100	-0.025***	0.002	-0.017***
	(0.010)	(0.018)	(0.004)
OP1	0.012	-0.001	0.004
	(0.020)	(0.026)	(0.006)
CPU*OP1	0.019	0.006	0.005
	(0.024)	(0.031)	(0.007)
OP2	-0.009	0.003	0.011*
	(0.021)	(0.026)	(0.006)
CPU*OP2	-0.002	-0.003	-0.007
	(0.026)	(0.026)	(0.008)
OP3	-0.016	-0.024	-0.019***
	(0.017)	(0.022)	(0.006)
CPU*OP3	0.022	0.024	0.017**
	(0.021)	(0.027)	(0.007)
OP4	0.008		0.033***
	(0.016)		(0.012)
CPU*OP4	-0.002	-0.094**	-0.051***
	(0.021)	(0.045)	(0.007)
OP5	0.058***		0.034***
	(0.017)		(0.012)
CPU*OP5	-0.060***	-0.028	-0.020*
	(0.021)	(0.058)	(0.011)
OP6	0.090***	-0.024	0.035**
	(0.031)	(0.024)	(0.015)
CPU*OP6	-0.089**	0.083**	0.013
	(0.037)	(0.034)	(0.018)

Table 8: Cont'd

	Pooled OLS (1)	Fixed effect (2)	Mixed effects (3)
Education	0.022***	0.003	0.024***
	(0.001)	(0.010)	(0.001)
Exp.	0.015***	0.089	0.016***
	(0.002)	(0.064)	(0.001)
Exp. ^2 /100	-0.025***	-0.017	-0.024***
	(0.005)	(0.038)	(0.002)
Seniority	0.007***	-0.010**	0.000
	(0.002)	(0.004)	(0.001)
Seniority ^2 /100	-0.009	0.013	0.004
	(0.006)	(0.029)	(0.003)
Black	-0.033		-0.050*
	(0.043)		(0.027)
Othraces	-0.021**		-0.020***
	(0.009)		(0.006)
Female	-0.102***		-0.107***
	(0.016)		(0.008)
Married	0.093***	0.039	0.073***
	(0.013)	(0.038)	(0.006)
Married*Female	-0.038**	-0.026	-0.037***
	(0.018)	(0.055)	(0.009)
Ptime	0.028	-0.033	-0.029***
	(0.023)	(0.047)	(0.009)
Union	0.061***	0.160**	0.078***
	(0.011)	(0.075)	(0.006)
Small size	0.038***	0.043**	0.051***
	(0.017)	(0.022)	(0.008)
Average size	0.136***	0.077***	0.112***
	(0.017)	(0.025)	(0.010)
Large size	0.189***	0.104***	0.173***
	(0.019)	(0.029)	(0.012)
Occupation dummies	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes
R-squared	0.527		
Sample size	34146	34146	34146

Statistical significance: *=10%; **=5%; ***=1%.
Robust standard errors in parentheses.

Table 9: Robustness Check to Other Specifications

	Pooled OLS		Mixed effects	
	(1)	(2)	(3)	(4)
Year	0.021**	0.022**	0.017***	0.018***
	(0.001)	(0.009)	(0.002)	(0.002)
Intercept	1.731***	1.856***	1.947***	2.001***
	(0.032)	(0.042)	(0.019)	(0.025)
CPU	0.129***	0.094***	0.057***	0.047***
	(0.017)	(0.011)	(0.006)	(0.006)
CAT	-0.022	0.023	-0.002	-0.001
	(0.017)	(0.013)	(0.005)	(0.005)
Othtech	-0.062***	-0.032	-0.017***	-0.013***
	(0.012)	(0.011)	(0.004)	(0.004)
Exp_cpu	0.015***	0.012***	0.011***	0.009***
	(0.003)	(0.002)	(0.001)	(0.001)
Exp_cpu ^2./100	-0.034**	-0.026**	-0.021***	-0.018***
	(0.015)	(0.010)	(0.004)	(0.004)
OP1		0.025**		0.008**
		(0.011)		(0.004)
OP2		-0.009		0.007*
		(0.012)		(0.004)
OP3		-0.002		-0.008**
		(0.010)		(0.004)
OP4		0.006		0.002
		(0.011)		(0.009)
OP5		0.019*		0.021**
		(0.011)		(0.009)
OP6		0.031*		0.044***
		(0.018)		(0.009)
Education	0.038***	0.022***	0.034***	0.024***
	(0.001)	(0.001)	(0.001)	(0.001)
Exp.	0.022***	0.015***	0.020***	0.016***
	(0.002)	(0.002)	(0.001)	(0.001)
Exp. ^2./100	-0.036***	-0.025***	-0.030***	-0.024***
	(0.005)	(0.005)	(0.002)	(0.002)

Table 9: Cont'd

	Pooled OLS		Mixed effects	
	(1)	(2)	(3)	(4)
Seniority	0.006***	0.007***	- 0.001	0.000
	(0.002)	(0.002)	(0.001)	(0.001)
Seniority ^2/100	-0.013***	-0.009	0.009**	0.004
	(0.006)	(0.006)	(0.004)	(0.003)
Black	-0.061	-0.034	-0.080***	-0.052*
	(0.046)	(0.043)	(0.029)	(0.027)
Othraces	-0.034***	-0.022**	-0.030***	-0.020***
	(0.011)	(0.009)	(0.006)	(0.006)
Female	-0.171***	-0.101***	-0.154***	-0.107***
	(0.015)	(0.016)	(0.008)	(0.008)
Married	0.138***	0.093***	0.090***	0.073***
	(0.015)	(0.013)	(0.007)	(0.006)
Married*Female	-0.066***	-0.038**	-0.050***	-0.037***
	(0.020)	(0.018)	(0.010)	(0.009)
Ptimes	-0.042	0.028	- 0.042***	-0.029***
	(0.029)	(0.023)	(0.009)	(0.009)
Union	0.047***	0.063***	-0.053***	0.079***
	(0.011)	(0.011)	(0.006)	(0.006)
Small size	-0.023	0.039**	0.043***	0.053***
	(0.019)	(0.017)	(0.009)	(0.008)
Average size	0.145***	0.138***	0.107***	0.113***
	(0.019)	(0.017)	(0.010)	(0.010)
Large size	0.245***	0.188***	0.179***	0.174***
	(0.021)	(0.019)	(0.012)	(0.012)
Occupation dummies	No	Yes	No	Yes
Industry dummies	No	Yes	No	Yes
R-squared	0.407			
Sample size	34146	34146	34146	34146

Statistical significance: *=10%; **=5%; ***=1%.
Robust standard errors in parentheses.

Table 10: Robustness Check to Sample Selection

	Pooled OLS (1)	Fixed effect (2)	Mixed effects (3)
Year	0.024***	-0.021	0.017***
	(0.008)	(0.044)	(0.002)
Intercept	1.845***	1.850**	1.943***
	(0.037)	(0.802)	(0.023)
CPU	0.084***	-0.009	0.039***
	(0.013)	(0.032)	(0.005)
CAT	0.012*	0.002	0.003
	(0.012)	(0.014)	(0.004)
Othtech	-0.029***	0.003	-0.005
	(0.012)	(0.013)	(0.003)
Exp_cpu	0.012***	0.001	0.009***
	(0.002)	(0.004)	(0.001)
Exp_cpu ^2 /100	-0.026***	- 0.000	-0.020***
	(0.009)	(0.017)	(0.004)
Education	0.025***	-0.011	0.024***
	(0.001)	(0.011)	(0.001)
Exp.	0.015***	0.068	0.017***
	(0.002)	(0.050)	(0.001)
Exp. ^2 /100	-0.025***	-0.025	-0.026***
	(0.004)	(0.034)	(0.002)
Seniority	0.008***	-0.008	0.002***
	(0.002)	(0.005)	(0.001)
Seniority^2 /100	-0.011*	0.002	-0.000
	(0.006)	(0.032)	(0.003)
Black	-0.015		-0.047*
	(0.038)		(0.026)
Othraces	-0.008		-0.017***
	(0.009)		(0.006)

Table 10: Cont'd

	Pooled OLS	Fixed effects	Mixed effects
	(1)	(2)	(3)
Female	-0.107***		-0.109***
	(0.014)		(0.007)
Married	0.101***	0.040	0.077***
	(0.013)	(0.035)	(0.006)
Married*Female	-0.037**	-0.007	-0.030***
	(0.017)	(0.048)	(0.009)
Part-time	0.027	-0.030	-0.015*
	(0.019)	(0.047)	(0.008)
Union	0.060***	0.145*	0.074***
	(0.011)	(0.074)	(0.006)
Small size	0.053***	0.052**	0.081***
	(0.012)	(0.022)	(0.007)
Average size	0.158***	0.085***	0.147***
	(0.011)	(0.025)	(0.008)
Large size	0.240***	0.113***	0.213***
	(0.013)	(0.029)	(0.010)
Occupation dummies	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes
R-squared	0.516		
Sample size	41807	41807	41807

Statistical significance: *=10%; **=5%; ***=1%.
Robust standard errors in parentheses.

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