How Do Computers and Internet Affect Employee Compensation?

A Report Submitted to Harry Bridges Center for Labor Studies

Ming Fan
Department of Information Systems & Operations Management
University of Washington Business School
Seattle, WA 98195-3200
mfan@u.washington.edu

Debabrata Dey
Department of Information Systems & Operations Management
University of Washington Business School
Seattle, WA 98195-3200
ddey@@u.washington.edu

Gang Peng
Department of Information Systems & Operations Management
University of Washington Business School
Seattle, WA 98195-3200
gangpeng@u.washington.edu

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1. Introduction

Studies have documented the skill-biased technological change (SBTC) throughout the twentieth century that has caused changes in the relative productivity of various types of workers and has shifted the demand toward more skilled workers (Autor et al. 1998, Goldin and Katz 1998). Information technology (IT) is the largest and most widespread technical change in the past two decades (Bresnahan et al. 2002) and has enabled organizational transformations, often resulting in higher productivity and efficiency (Brynjolfsson and Hitt 1996, Brynjolfsson et al. 2002, Devaraj and Kohli 2003). While studies on IT payoff are generally at the level of the firm or the industry, research on returns of IT at individual level has received little attention in information systems (IS) literature with the exceptions of the studies by Talmor and Wallace (1998) and Anderson et al. (2000) on executive compensation in the IT industry and the work by Ang et al. (2002) and Mithas and Krishnan (2004) on compensations for IT professionals.

The impact of computer and Internet use on worker compensation is an important theoretical and managerial issue. In recent decades, income disparities in the U.S. have grown sharply (Koretz 2003). Workers with limited education and skills are facing diminishing job opportunities and earning prospects. The growing use of computers has affected the job market immensely and has contributed to the widening income gap (Krueger 1993, Katz 1996). There have been a few previous studies on the return of computer use on wages for the general workforce with somewhat contradictory findings (Krueger 1993, DiNardo and Pischke 1997, Entorf and Kramarz 1997, Entorf et al. 1999). The magnitude of the impact of computer use on wages is unclear. It is also unclear whether the return of computer use on wages is really a return for computer skills, or whether it reflects a return for unobservable personal ability (DiNardo and Pischke 1997). Some studies attribute the computer use wage premium to SBTC and the increased demand of highly educated workers (e.g. Krueger 1993), while others suggest that technology could be "deskilling" and result in lower wages (e.g. Braverman 1974, Cappelli 1996).

Understanding the mechanisms behind the computer and Internet use and wage relationship is important because it has a profound impact on the decisions of individuals, organizations, and policy makers on future investments in technology and education. We posit that the computer and Internet use and wage relationship can only be understood by examining how computers are put to different uses in the workplace and how computer and Internet use is accompanied with organizational changes.

This study aims to explain the mechanisms through which computers affect wage structures in the U.S. Specifically, we examine the effects of computer and Internet use and task complementarity, generic versus specialized computer tools, and changes in the workplace. Our study provides an important extension of IT productivity research to individual level. We also study technology use and wage returns in Washington State.

The following is a summary of the major findings:

- The study extends the theoretical framework on non-routine job tasks (Autor et al. 2003) and looks inside the black box of computer-use wage premium. The effects of computer and Internet use are not homogeneous across the workplace. Computers complement non-routine tasks but substitute routine tasks. We find that the complementarity between computer and Internet use and non-routine tasks is a major factor in computer-use wage premium.

- We assess computer and Internet use and wage structure in the broad framework of new work practices and changing skill requirements for workers. Our results suggest that the effects of computer and Internet use on wage largely depend on the changes in work practices that accompany technology use.
- We compare the results between Washington State and national average. The findings provide interesting policy implications for Washington State.

The remainder of this report proceeds as follows: Section 2 reviews related prior work in this area and develops testable hypotheses from existing theories. Section 3 describes our datasets, the panel matching methodology, and the estimation models. Estimation results and analyses are presented in Section 4. Specific findings from Washington State are presented in Section 5. Conclusions are offered in Section 6.

2. Theory

2.1 Literature and Research Questions

Researchers have long been interested in the growing use of IT in businesses. IT has become ever more important as computing technology increases in power and expands its scope beyond back-office support to its current pervasive role in firms (Bresnahan et al. 2002). An important research question is whether computer use has affected wage structure. Krueger (1993) examines whether workers who use computers at work earn more as a result of applying their computer skills. Based on a cross-sectional CPS dataset from 1984 and 1989, he finds that workers are rewarded 10-15 % higher if they use computers at work. However, a well-known problem for cross-sectional analysis here is that of the omitted variable bias. For example, among the omitted variables, individual ability is a major factor in determining one's wage level. Workers with higher abilities could be the ones who are more likely to use computers, and a cross-sectional analysis could overestimate the impact of computer use on wage levels.

DiNardo and Pischke (1997) question whether the wage premium on computer use is really a return to skills, or whether it reflects the fact that higher-wage workers simply happen to use computers more at work, and the high return is actually a return for higher ability. Using a German cross-sectional dataset, they replicate Krueger's study and find that measured wage differentials associated with pencils and calculators are of the same magnitude as those with computers. Since it is difficult to attribute substantial rewards to pencil usage, their findings cast serious doubt on whether using computers can attract any wage premium at all. The arguments, however, are not fully convincing because their results show that the coefficient of pencil use become insignificant over time whereas the coefficient of computer use remains robust.

Entorf and Kramarz (1997) and Entorf et al. (1999) apply a panel data to control for individual heterogeneity. They use a three-year French labor force survey data and conclude that there is no return for using technologies, and the premium is largely from individual heterogeneity. However, their results are limited in two ways: First, their definition of technology use is too broad, and consequently their results cannot be compared with those from the aforementioned studies. Second, their use of discretized income data makes their results less accurate.

One of the objectives of this study is to accurately estimate the wage premiums resulting from computer and Internet use by controlling the effect of omitted variable bias such as individual ability. However, a more intriguing and more important research issue is the explanation of mechnisms through which computer and Internet use affects wage structure in practice. Few studies have directly studied these mechanisms. Krueger (1993) attributes computer use wage premium to SBTC, which have shifted the demand of labor toward highly skilled and educated workers. As demand for more educated workers increases, wage level is likely to increase as well. We take a different approach and point that the computer use and wage relationship can only be understood clearly by examining how computers and Internet have changed the workplace. Firms do not achieve efficiency gains by simply plugging in computers and IT equipment. Instead, they go through organizational redesign and make changes to their products and processes (Bresnahan et al. 2002). Thus, assessment of computer use and wage relationship should examine how computers are put to different uses and how computer use is accompanied with new work practices and changing skill requirements for individual workers in the workplace.

Prior studies in this area mostly rely on measures such as education and job hierarchy (blue-collar or white-collar) to study the relationship between technology and changes in the workplace. The mechanism of that relationship is not all that clear. For example, white-collar is a label that presupposes an essential difference between the structure of labor in the factory and in the office. In reality, some blue-collar jobs may require far more skills than many white-collar jobs (Rumberger 1981). Our task- and workplace-based approach allows us to examine how computers have affected job contents in the American workplace, and provides an important extension of IT productivity research to individual level.

2.2 Computer Use and Non-routine Tasks

Empirical studies have provided evidence of robust correlation between the use of computer-based technologies and increased demand for educated workers. However, SBTC theory does not provide clear explanations on what constitutes the complemenatrity between computer use and education, and what causes skilled workers to be relatively more in demand and to have a potentially higher wage.

Autor et al. (2003) develop a framework to examine work as a series of tasks. Routine tasks include both manual and cognitive tasks that follow well-defined, explicit rules, which makes them easily programmable. Since computers can perform repetitive activities more efficiently, routine tasks are subject to substitution by computers. Non-routine tasks, such as problem-solving and complex communication, are, on the other hand, not well-defined and hence not programmable. Computer technology, at least at the current state of the art, is a relatively poor substitute for the mental capabilities of people in carrying out non-routine tasks. Rather than replacing human brains, computers complement users in performing non-routine tasks, both analytical and interactive.

We can understand that computer use contributes to employee wages in two ways. First, according to human capital theory (Mincer 1974), earnings are payoff to human capital; knowledge and skills, which come from education and training, generate a certain stock of productive capital. As employers hire workers with computer skills or invest in training to help workers to acquire skills to use computers at work, they expect those workers to be more productive and are likely to increase the price---wage---for those skills. Meanwhile, as employees also invest their time and effort to acquire new skills to use computers on the job, they expect a higher wage as well.

Second, as suggested in the task model (Autor et al. 2003), the effects of computer use on different tasks are uneven and computers complement non-routine tasks. The complementarity mechanism has two effects: (i) With two complementary activities in a production process, a decrease in the price of one causes an increase in the demand for the other (Milgrom and Roberts 1992). As the price of computer capital fell in recent decades, it has raised relative demand for workers who have expertise in performing non-routine tasks. (ii) In a group of complementary activities, an increase of any one activity increases the marginal productivity of another (Milgrom and Roberts 1992). As a result, workers who perform non-routine tasks tend to gain larger benefits in using computers as technologies become more pervasive. This is because the opportunities for "co-inventions" by applying technologies in the workplace are greater for these workers compared to those who perform mostly routine tasks (Brynjolfsson 2003). Therefore, task characteristics should moderate how computers contribute to an individual's productivity. According to efficiency wage theory, firms usually pay wage premiums to attract qualified employees and to serve as an incentive mechanism to elicit greater productivity from workers.

2.3 Generic versus Specialized Tools

As a general purpose technology, computers complement non-routine tasks because of their pervasiveness in adoption and their ability to spawn innovation and co-inventions (Bresnahan and Trajtenberg 1995, Jovanovic and Rousseau 2005). However, at any given time, not all computer tools are adopted evenly. Using the criterion of pervasive adoption, we classify computer applications into two catogories: generic tools and specialized tools. Table 1 lists different computer applications used at a modern workplace and the levels of their adoption by employees in different occupation groups. It is clear from this table that word processing, email, scheduling, and spreadsheet applications are consistently used across different occupation groups. These tools are consistently applied across different industries as well. We classify these applications as generic tools. On the other hand, it is clear from Table 1 that graphic design and programming have an uneven and an overall low adoption rate; these are classified as specialized tools.

The complementarity relationship between computer use and non-routine tasks must be understood dynamically. In the long run, declines in the price of computers cause the demand for its complements to shift out. In any particular short run, only a subset of firms will have achieved the full potential of the complementarity (Bresnahan et al. 2002) and only a subset of technologies will have enabled task transformation in the workplace. In order for the complementarity mechanism between computer use and non-routine task to function, certain computer tools have to be adopted widely. A wider adoption of those tools will increase the demand and productivity of workers who perform non-routine tasks. Also, the increased level of performance of the workers who carry out non-routine tasks will further increase the marginal returns and demand of those generic tools. Thus, the pervasive adoption of certain computer tools will create a positive feedback loop between the two complementary activities (Milgrom and Roberts 1992). On the other hand, because of higher learning cost or other reasons, if the adoption of certain computer tools does not reach a critical mass, this positive feedback loop becomes hard to materialize.

Table 1: Adoption levels of Different Computer Applications at Work

Occupation Groups	Internet & Email	Word Processing	Scheduling	Spreadsheet	Graphic Design	Programming
Executive, administrative & managerial	83.70	79.46	64.00	76.82	34.28	16.41
Professional specialty	82.14	78.07	55.27	63.47	39.60	19.74
Technicians & related support	70.77	59.17	51.34	60.81	29.17	26.16
Sales occupations	69.02	59.79	47.95	59.96	25.14	11.02
Administrative support, including clerical	65.95	66.37	47.37	30.36	18.81	9.67
Services occupations	50.62	52.96	45.19	44.66	17.84	8.79
Precision production, craft & repair	59.80	45.90	43.80	51.68	22.78	17.17
Machine operators, assemblers & inspectors	42.14	36.61	27.85	41.06	20.89	11.52
Transportation & moving equipment	42.45	36.23	40.00	40.75	14.72	8.49
Handlers, equipment cleaners, helpers & labors	44.06	33.79	30.59	40.64	14.61	11.19
Farming, forestry &fishing	64.96	61.16	40.63	59.82	24.11	9.15

Notes: Authors' tabulation of CPS 2001 Computer and Internet Use Supplement as a percentage of total computer users; N =38, 220.

2.4 New Work Practices and Changing Skill Requirements

Rapid computer use in the late twentieth century in the U.S. has enabled immense organizational changes. The common theme of the new work practices is that they represent a contrast to Tayloristic work systems associated with functional specialists, and favor more decentralized and horizontal organizations with workers performing multiple tasks, working in teams, performing quality inspection, and solving semistructured problems (Murnane and Levy 1996, Cappelli 1996, Doms et al. 1997). For example, enterprise systems enable individual workers to have the necessary information to complete an entire process that was historically fragmented (Hammer 1990). In manufacturing, the use of flexible manufacturing processes and "lean" production is often coupled with greater worker discretion (Capelli 1996). These new work practices aim to increase the quality, productivity, and flexibility by encouraging employees to have a higher level of accountability. In particular, decision-making is transferred down the hierarchy to employees or to their teams, and workers need to become adept at multiple tasks, work in teams, and take responsibility for quality control (Applebaum and Batt 1994, Cappelli 1996). Efficiency wage theory suggests that firms generally have to pay higher wages in order to motivate these workers to devote higher level of effort and take more responsibilites (Baker 1992).

Scholars have long been debating whether and how computerization and organizational changes have altered skill requirement in the workplace (Cappelli 1996). Computerization and new work practices have enabled transformation of many jobs. For example, production and clerical jobs could evolve from specialized tasks with little decision-making responsibilities to more broadly defined jobs with higher levels of accountability. This has created a demand for a set of new skills for workers under the new work practices. The new skills are comprised of "soft skills" such as communication and interactive skills and "hard skills" such as numerical and analytical skills (Applebaum and Batt 1994, Murnane and Levy 1996). Interactive skills are necessary for workers to work in a team-environment, to send and receive data between departments within an organization, and to communicate with external entities including customers and suppliers. Numerical and analytical skills are important to operate computerized equipments and interact with advanced information systems (ref). According to human capital theory, wages should be higher for workers with higher level of knowledge and skills (Mincer 1974).

3. Data and Methodology

3.1 Data

The data used in this study come from three sources: (i) the Current Population Survey (CPS) administered by the U.S. Census Bureau and the Bureau of Labor Statistics, (ii) the Dictionary of Occupational Titles (DOT) created and published by the U.S. Department of Labor, and (iii) the unemployment rates from the Bureau of Labor Statistics.

The Current Population Surveys have been conducted monthly for over 50 years. They constitute the primary source of official government statistics on the labor force characteristics of the U.S. population. They include a basic monthly survey and supplementary surveys on various topics. The basic monthly survey provides direct measurement of employment status each month on the basis of a random sample of the U.S. population. The supplementary surveys of CPS are designed to meet a variety of additional needs and are conducted as needed in a particular month to gather in-depth information on specific aspects of the labor force. In August 2000 and September 2001, two supplementary surveys focusing on computer and Internet usage were conducted. The 2000 supplementary survey focuses on Internet usage. It has a sample size of

134,986, among which 60,608 are employed workers. The 2001 survey has questions on general computer use in addition to Internet usage. It has a sample size of 158,865, among which 70,617 are employed workers. We make use of the datasets obtained through both these surveys.

Dictionary of Occupational Titles (DOT) was originally created by the U.S. Department of Labor in 1939 to measure occupational skills and to match job applicants to jobs (Cain and Treiman 1981). DOT contains more than 12,000 detailed occupations, which are scored on 44 variables, including such dimensions as training time, aptitude, temperament, interest, physical demand, and environmental condition. An important characteristic that distinguishes the DOT scores from others is that DOT scores are based on extensive on-site observation by job analysts using standardized criteria. This makes the DOT scores more accurate and objective when compared to self-reported scores. As a result, these scores are used extensively in sociology and economics research (Rumberger 1981, Autor et al. 2003). In order to match it with the CPS dataset, DOT scores are aggregated at the Census occupations level; this is analogous to the approach used by previous studies (England and Kilbourne 1988, Autor et al. 2003).

Since wages are prices for labor, we should control unemployment rates to reflect the supply and demand effects in the labor market. The unemployment data are provided by the Bureau of Labor statistics, and it includes the unemployment rates in year 2000 and 2001 for 51 detailed industries (excluding Armed Forces) included in the CPS.

CPS surveys use a rotation-sampling technique. Each household address has a unique ID (HHID), and each individual in the household is identified by a line number (LineNo). To control for migration, a third variable, HHNUM, is used. HHNUM is initialized at one and is incremented by one every time a new family moves in at the same household address. In order to construct the panel dataset, it is necessary to match or link the same individual from the two supplementary surveys (Madrian and Lefgren 2002). We use HHID, LineNo, HHNUM, as well as additional variables (gender, race, region, and metropolitan area), to match the individuals in 2000 and 2001 CPS datasets. The matching process leads to a sample size of 10,623 individuals in the two-year panel dataset used in this study.

3.2 Variables

In order to be consistent with previous research and theory (Mincer 1974), we use log wage rate as dependent variable in the individual earning function. Wage determinants are mainly from three strands of theory: human capital theory (Mincer 1974), compensating wage differentials theory (Rosen 1986), and labor market discrimination theory (Becker 1971). Following these theories, we include standard worker characteristics such as education, experience, gender, race, marital status, union status, region, veteran status, occupation, and metropolitan area, which are available from the CPS dataset. In the individual earning function, log wage is found to be concave on worker experience. Thus, experience takes a quadratic form in the function (Mincer 1974).

We use the same measure of non-routine tasks by each occupation (NRTP) developed by Autor et al. (2003). This definition of non-routine tasks have been well accepted in economics and labor studies (see, for example, Baily and Lawrence 2004, Borghans and ter Weel 2004, Egger and Grossmann 2005, Maurin and Thesmar 2004, Wheeler 2005).

Computer and Internet use variables are available directly from the 2000 and 2001 supplementary surveys. In this study, the independent variable, computer and Internet use, is coded as one if an individual use both computer and Internet at works, so it is slightly different from the independent variable, computer use, in Krueger's study (1993), where computer use is coded as one if an individual uses only computer at work, not matter he/she uses Internet or not. Different computer usage variables are directly from the 2001 supplementary survey. We develop the measure for generic and specialized computer tools following studies on GPTs (e.g. Bresnahan and Trajtenberg 1995). A computer tool is considered ``generic'' if it can be applied across different occupations. Based on the computer usage data (see Table ref {tb:skillpct}), word processing, email, scheduling, and spreadsheet belong to generic computer tools. Graphic design and programming are classified as specialized tools.

Five different DOT variables are used to measure occupational input: DCP, MATH, STS, FINGDEX, and EYEHAND. DCP stands for direction, control, and planning, and measures non-routine interactive inputs. MATH measures quantitative reasoning requirement and thus non-routine analytical inputs. STS measures routine cognitive inputs by considering work requiring set limits, tolerances, or standards. FINGDEX stands for finger dexterity and measures routine manual inputs. Finally, EYEHAND stands for eye-hand-foot coordination, thus measuring non-routine manual inputs. Based on these five variables, the non-routine task percentage for each occupation is calculated as:

$$\text{NRTP} = \frac{\text{nonroutine score}}{\text{routine score + nonroutine score}} \text{ x } 100\%$$

where routine score = STS + FINGDEX, and nonroutine score = DCP + MATH + EYEHAND.

In labor studies, skills can refer to the abilities and human capital that workers bring to jobs, or to the specific demands that individual jobs require (Rumberger 1981, Cappelli 1993). We take the second approach. We use three variables from DOT to represent new work practices and skill requirements (U.S. Department of Labor, 1972). The variable VARCH from DOT is used in our study to measure job accountability (ACC). VARCH is defined as job adaptability to perform a variety of duties and the ability to interpret firm policies, adjust work procedures, and resolve problems. The DOT variable DEPL is employed to measure interactive skills (ITA). DEPL stands for the ability to deal with people, cooperate with other workers, contact others in successful meaner, and work as a team member. The variable NUMERICAL is used to measure numerical and analytical skills (NUM). It measures the capacities to understand and use mathematical principles to solve problems. For example, workers should be able to use mathematical formulas and equations to conduct cost analysis.

3.3 Estimation Models

We start with ordinary least square (OLS) as the basic estimation model. Similar to Krueger (1993), one could augment a traditional cross-sectional earnings function for individual *i* with a dummy variable: I_i is one if individual *i* uses computer and Internet at work, and zero otherwise. Adopting the traditional log-linear specification, one would then obtain the following OLS model for examining the effects of computer and Internet use on the wage W_i of individual *i*:

$$ln(W_i) = \beta_0 + I_i\beta_1 + \mathbf{X}'_i\,\gamma + \varepsilon_i$$

where $\mathbf{X}_i$ is the column vector of other wage determinants such as education, age, and ε_i is the error term.

A potential problem in employing an OLS model is that of the omitted variables bias, which could result in biased estimates of the coefficients (Wooldridge 2002). In this study, for example, individual ability cannot be directly observed even though this variable is clearly an important determinant of an individual's wage. Since individual ability is likely to be correlated with computer and Internet use, β_1 would be overestimated in the OLS model and the estimation of the other coefficients could be biased as well.

A possible solution to this problem is the use of panel data containing repeated observations about the same individuals over two or more time periods. As mentioned earlier, I constructed such a panel dataset by matching the 2000 and 2001 CPS datasets. Assuming that the ability of individual *i*, denoted u_i, remains unchanged between 2000 and 2001 (the sampling time period), I propose to use the following fixed effects model:

$$ln(W_{it}) = I_{it}\beta_1 + \mathbf{X}'_{it}\,\gamma + u_i + \varepsilon_{it}$$

where I_{it} is one if individual i used computer and Internet in year *t*, and $t \in \{2000, 2001\}$. This way, we can difference out the individual ability over the two periods and obtain a consistent estimate of β_1. Before applying the fixed effects model in Equation (4.1), it is, however, necessary to ascertain that u_i is correlated with the other independent variables; otherwise the random effects model would be more efficient (Verbeek 2004, Wooldridge 2002).

Although the fixed effects model provides consistent estimates, there is an important limitation. The fixed effects model accounts for the unobserved individual ability by differencing out—and thereby excluding—all the other time-invariant independent variables such as gender, race, education, and geographic region, which are also of interest to us. The Hausman-Taylor model (Hausman and Taylor 1981) provides a solution to this problem. A typical specification of the Hausman-Taylor model is (Verbeek 2004):

$$\ln(W_{it}) = \mathbf{X}'_{1it}\,\gamma_1 + \mathbf{X}'_{2it}\,\gamma_2 + \mathbf{Z}'_{1i}\,\gamma_3 + \mathbf{X}'_{2i}\,\gamma_4 + u_i + \varepsilon_{it}$$

where the **X**-variables are all time-variant and the **Z**-variables are all time-invariant. The variables with subscript 1 ($\mathbf{X}_{1it}, \mathbf{Z}_{1i}$) are uncorrelated with u_i and all ε_{it}, whereas the variables with subscript 2 ($\mathbf{X}_{2it}, \mathbf{Z}_{2i}$) are correlated with u_i, but not with any ε_{it}. Hausman and Taylor (1981) propose a two-step estimation procedure: The first step performs a feasible generalized least square (FGLS) transformation of the model. In the second step, $\mathbf{X}_{1it} - \bar{\mathbf{X}}_{1i}$, $\mathbf{X}_{2it} - \bar{\mathbf{X}}_{2i}$, $\mathbf{Z}_{1i}$ and $\bar{\mathbf{X}}_{1i}$ are all used as instruments to get consistent and efficient estimates of the coefficients, where . We employ the Hausman-Taylor model where:

$\mathbf{X'}_1$ = (Experience, Experience^2, Married, Union member, Veteran status, Unemployment rate),

$\mathbf{X'}_2$ = (I, Full-time, NRTP),

$\mathbf{Z'}_1$ = (Male, Metropolitan area, Black, Other race),

$\mathbf{Z'}_2$ = (Education).

Prior work in labor studies provides ample theoretical justification for why the variables in $\mathbf{X}_1$ and $\mathbf{Z}_1$ are uncorrelated with the unobserved individual ability (Hausman and Taylor 1981, Chowdhury and Nickell 1985, Keith and Malone 2005).

We generate an interaction term between computer and Internet use at work and the level of nonroutine tasks, and estimate the following Hausman-Taylor model:

$$\ln(W_{it}) = I_{it}\text{NRTP}_{it}\alpha_1 + \mathbf{X'}_{1it}\gamma_1 + \mathbf{X'}_{2it}\gamma_2 + \mathbf{Z'}_{1i}\gamma_3 + \mathbf{X'}_{2i}\gamma_4 + u_i + \varepsilon_{it},$$

where ($\mathbf{X}_1, \mathbf{X}_2, \mathbf{Z}_1$, and $\mathbf{Z}_2$) are as before.

We also introduce two dummy variables—G_i and S_i. G_i (S_i) is one if individual i uses generic (specialized) computer tools and zero otherwise. As the detailed computer usage data (world processing, scheduling, spreadsheet, graphic design, and programming, etc.) are only available in year 2001, we employ the following OLS model:

$$ln(W_i) = \beta_0 + G_i\beta_2 + S_i\beta_3 + G_i\text{NRTP}_i\beta_4 + S_i\text{NRTP}_i\beta_5 + \mathbf{X'}_i\gamma + \varepsilon_i.$$

It should be noted that the original computer and Internet use dummy, I_i, is directly related to G_i and S_i. Therefore, in order to avoid multi-collinearity, I_i is not included in the above model.

We estimate the following set of Hausman-Taylor models with interaction terms:

$$\ln(W_{it}) = \text{ADP}_{it}\alpha_2 + I_{it}\text{ADP}_{it}\alpha_3 + \mathbf{X'}_{1it}\gamma_1 + \mathbf{X'}_{2it}\gamma_2 + \mathbf{Z'}_{1i}\gamma_3 + \mathbf{Z'}_{2i}\gamma_4 + u_i + \varepsilon_{it}$$

$$\ln(W_{it}) = \text{INT}_{it}\alpha_4 + I_{it}\text{INT}_{it}\alpha_5 + \mathbf{X'}_{1it}\gamma_1 + \mathbf{X'}_{2it}\gamma_2 + \mathbf{Z'}_{1i}\gamma_3 + \mathbf{Z'}_{2i}\gamma_4 + u_i + \varepsilon_{it}$$

$$\ln(W_{it}) = \text{NUM}_{it}\alpha_6 + I_{it}\text{NUM}_{it}\alpha_7 + \mathbf{X'}_{1it}\gamma_1 + \mathbf{X'}_{2it}\gamma_2 + \mathbf{Z'}_{1i}\gamma_3 + \mathbf{Z'}_{2i}\gamma_4 + u_i + \varepsilon_{it}$$

where ADP_{it} is the measurement of degree of adaptability, INT_{it} the interactive skill, and NUM_{it} the numerical skill, associated with the occupation of individual i in year t. These three variables are all time-variant and correlated to u_i.

4. Results at the National Level

We perform several tests to verify the appropriateness of the model specifications used in this research. We first confirm that the individual effects (u_i) are significant in the panel models. To test this, we use the LM test proposed by Breusch and Pagan (1980). Under the null hypothesis that the individual effects are not significant, the LM-statistic is distributed as χ_1^2. The LM-statistic for Equation (4.1) is 1806.76, which is much higher than $\chi^2_{1;0.001}$ =10.83. This indicates that individual effects are quite significant, and the OLS model is not appropriate in this case (Greene 2003).

We next test whether the individual effects are correlated with the independent variables; if they are not correlated, then a random effects model would be more efficient (Wooldridge 2002). We use the Hausman test (Hausman 1978) for this purpose. The test statistic, which is based on the difference between the fixed and random effects estimators, follows a χ^2_K distribution, where *K* is the number of time-variant independent variables. In Equation (4.1), K = 9, and the test statistic is 454.77, which far exceeds $\chi^2_{9;0.001}$=27.88. This confirms the appropriateness of the fixed effects model (over the random effects model) specification.

Next, we conduct specification tests for the Hausman-Taylor models. Under the null hypothesis that the variables in $\mathbf{X}_1$ and $\mathbf{Z}_1$ are uncorrelated with the individual ability (u_i), the Hausman-Taylor test statistic follows a χ^2_L distribution, where $L = \min\{k_1 - g_2, N - K\}$, k_1 is the number of time-variant independent variables uncorrelated with u_i, g_2 is the number of time-invariant independent variables correlated with u_i, *N* is the number of observations, and *K* is the number of time-variant independent variables (Hausman and Taylor 1981). The Hausman-Taylor test statistics are obtained for each of the above specifications; they are: 5.593 for Equation (4.2), 5.732 for Equation (4.3), 5.603 for Equation (4.5), 6.255 for Equation (4.6), and 4.764 for Equation (4.7). In each case, $L = k_1 - g_2$= 6 − 1 = 5, and the test statistics are all well below $\chi^2_{5;0.1}$ =9.24. Therefore, the Hausman-Taylor specification is an appropriate choice in each of these cases.

Finally, we test for multi-collinearity among the independent variables in the models. This is done by calculating the *variance inflation factor* (VIF) for all the independent variables, excluding the interaction terms. We find that the mean VIF-value (1.34) is only slightly higher than one, and the individual VIF-values are all well below the threshold of 10. Consequently, multi-collinearity should not be a problem in the specifications (Neter et al. 1996).

The results of the fixed effects model and the Harsman-Taylor models are presented in Table 2. The fixed effects model predicts that using computers and the Internet at work brings a wage premium of about 3.6% ($e^{0.035} - 1$). The corresponding premium estimated by the Hausman-Taylor model is about 4.5% ($e^{0.044} - 1$). These results do not suffer from the omitted variable bias present in some of the previous studies (e.g., Krueger 1993) and are, therefore, more accurate.

Table 2: Effects of Computer and Internet use and Nonroutine Tasks on Wage

Dependent variable: ln(Wage)	Fixed Effects	Hausman-Taylor	Hausman-Taylor
Intercept	1.587***	0.242**	0.247**
	(0.109)	(0.097)	(0.097)
Computer/ Internet use at	0.035***	0.044***	0.014
work	(0.009)	(0.007)	(0.018)
Education		0.121***	0.121***
		(0.007)	(0.007)
Experience	0.063***	0.023***	0.022***
	(0.008)	(0.001)	(0.001)
Experience^2/100	−0.074***	−0.033***	−0.033***
	(0.016)	(0.003)	(0.003)
Male		0.245***	0.245***

		(0.010)	(0.010)
Married	−0.011	0.074***	0.074***
	(0.032)	(0.013)	(0.013)
Union member	0.058***	0.074***	0.074***
	(0.014)	(0.009)	(0.009)
Full-time worker	0.095***	0.095***	0.095***
	(0.016)	(0.014)	(0.014)
Metropolitan area		0.135***	0.135***
		(0.011)	(0.011)
Veteran status	−0.128***	−0.038**	−0.037**
	(0.047)	(0.015)	(0.015)
Black		−0.090***	−0.090***
		(0.016)	(0.016)
Other races		−0.047**	−0.047**
		(0.021)	(0.021)
Unemployment rate	−1.209***	−0.405*	−0.403*
	(0.314)	(0.243)	(0.242)
Non-routine tasks	0.145***	0.148***	0.129***
	(0.026)	(0.023)	(0.025)
Computer/Internet use at work × non-routine tasks			0.054*
			(0.031)
R^2	0.057	0.377	0.377
ρ	0.749	0.685	0.686

Notes: N = 10,623. *p <0.1; **p < 0.05; ***p < 0.01.

The results on the impacts of the use of generic and specialized tools are in Table 3. As expected, the interaction between generic computer tools and non-routine task is highly significant, while the interaction between specialized computer tools and non-routine task is not significant.

The results on the effects of advanced skill requirements on wage returns are presented in Table 4. The interaction between computer and Internet use and adaptability is significant, and so is the interaction between computer and Internet use and interactive skills. However, the interaction between computer and Internet use and numerical and analytical skills is not significant.

Our results suggest that workers who use computers at work indeed command a wage premium. This, of course, implies that there must be employee-level productivity gains commensurate with this wage premium. These individual productivity gains collectively lead to better efficiency and effectiveness in different functional areas within an organization. In this sense, this research extends prior research on IT productivity to an individual level. We also find this wage premium is only available for performing non-routine tasks. When the percentage of non-routine tasks falls below a certain level, the impact of computer use on wage becomes insignificant. The results suggest that the complementarity between computer use and non-routine tasks may well be the underlying factor in explaining the computer-use wage premium.

Table 3: Estimated Coefficients for Returns to Computer Skills

Dependent variable: ln(Wage)	
Intercept	0.923***
	(0.015)
Education	0.066***
	(0.001)
Experience	0.021***
	(0.001)
Experience^2/100	–0.034***
	(0.001)
Male	0.220***
	(0.004)
Married	0.087***
	(0.005)
Union member	0.113***
	(0.006)
Full-time worker	0.192***
	(0.005)
Metropolitan area	0.128***
	(0.004)
Veteran status	–0.013**
	(0.007)
Black	–0.105***
	(0.007)
Other races	–0.006
	(0.009)
Unemployment rate	–1.367***
	(0.111)
Non-routine tasks	0.108***
	(0.013)
Generic computer tools	0.065***
	(0.011)
Specialized computer tools	0.086***
	(0.016)
Generic computer tools × non-routine tasks	0.191***
	(0.020)
Specialized computer tools × non-routine tasks	–0.037
	(0.026)
R^2	0.425

Notes: N =52,962. p<0.01.

Table 4: Effects of Computer and Internet use, New Work Practices, and Changing Skill Requirements

Dependent variable: ln(Wage)	Adaptability	Interactive Skills	Numeric Skills
Intercept	0.230**	0.252***	0.208**
	(0.097)	(0.097)	(0.096)
Computer and Internet use at work	0.032***	0.025*	0.023
	(0.011)	(0.014)	(0.026)
Education	0.126***	0.123***	0.115***
	(0.007)	(0.007)	(0.007)
Experience	0.022***	0.023***	0.022***
	(0.001)	(0.001)	(0.001)
$\text{Experience}^2/100$	–0.032***	–0.033***	–0.033***
	(0.003)	(0.003)	(0.003)
Male	0.247***	0.254***	0.246***
	(0.010)	(0.010)	(0.009)
Married	0.077***	0.078***	0.073***
	(0.013)	(0.013)	(0.012)
Union member	0.073***	0.074***	0.091***
	(0.009)	(0.009)	(0.009)
Full-time worker	0.096***	0.096***	0.090***
	(0.014)	(0.014)	(0.014)
Metropolitan area	0.137***	0.137***	0.125***
	(0.011)	(0.011)	(0.011)
Veteran status	–0.042***	–0.039***	–0.037**
	(0.015)	(0.015)	(0.015)
Black	–0.093***	–0.092***	–0.078***
	(0.017)	(0.016)	(0.016)
Other races	–0.055**	–0.052**	–0.050**
	(0.022)	(0.022)	(0.021)
Unemployment rate	–0.465*	–0.413*	–0.348
	(0.244)	(0.245)	(0.243)
Adaptability	0.001		
	(0.001)		
Interactive skill		0.003**	
		(0.001)	
Numeric skill			0.040***
			(0.004)
Computer and Internet use at work × Adaptability	0.004** (0.002)		
Computer and Internet use at work × Interactive skill		0.003* (0.002)	
Computer and Internet use at work × Numeric skill			0.003 (0.005)
R^2	0.371	0.372	0.398
ρ	0.690	0.684	0.677

Notes: N = 10,623. *p <0.1; **p < 0.05; ***p < 0.01.

5. Results for Washington State

We compare computer and Internet use and wage returns for Washington State and the national average. Although Washington State in general follows the national trend, there are many interesting differences. In addition, we find disparities in computer use and wage returns within the State.

5.1 Computer and Internet Use and Wage Returns in Washington State

As shown in Table 5, average wage is higher in Washington State than the nation. On average, a work in Washington State earned $16.75 per hour in 2001, 5% more than the national average of $15.94. Workers living in metropolitan areas of Washington State are paid even higher, earning $17.30 per hour.

One of the objectives of this study is to examine whether the use of computers and Internet has any effects on wage returns. We find that the percentage of workers that use computers and Internet at work in Washington State is 43.9% in 2001, about 11% more than the national average of 39.5%. Moreover, percent of nonroutine tasks is slightly higher in Washington State. On average, about 51% of the work tasks are nonroutine for workers in Washington State, compared to about 50% in the nation. The results suggest that Washington State workers not only use more technologies in the workplace, but also perform jobs that require higher level of skills. Therefore, it is likely that computer and Internet use and nonroutine tasks play important roles in contributing to higher wages in Washington State.

The regression results (Table 6) confirm that computer and Internet use contributes significantly to wage premium in Washington State. In addition, nonroutine task is also significant in contributing to higher wages in the State. Moreover, we can see

Table 5: Comparison of Washington State with National Average

Variables	National Average	Washington State	Washington State Metropolitan Area	Washington State Non-Metropolitan Area
Hourly wage	15.94	16.75	17.30	13.40
Computer/Internet use at work (%)	39.5	43.9	45.6	33.9
Nonroutine task (%)	50.2	51.1	51.3	50.0
DCP	2.91	2.99	3.06	2.56
MATH	3.86	3.93	3.98	3.64
STS	3.79	3.70	3.71	3.61

Table 6: Effects of Computer and Internet Use and Nonroutine Tasks on Wage, 2001

Dependent variable: ln(Wage)	U.S.	Washington State
Intercept	0.892***	1.100***
	(0.014)	(0.258)
Computer and Internet use at work	0.198***	0.216***
	(0.004)	(0.083)
Education	0.066***	0.039***
	(0.001)	(0.014)
Experience	0.021***	0.026**
	(0.001)	(0.011)
Experience^2/100	–0.034***	–0.048**
	(0.001)	(0.023)
Male	0.217***	0.232***
	(0.004)	(0.075)
Married	0.09***	0.184**
	(0.005)	(0.093)
Union member	0.116***	0.012
	(0.006)	(0.085)
Full-time worker	0.194***	0.054
	(0.005)	(0.094)
Metropolitan area	0.127***	0.075
	(0.004)	(0.093)
Veteran status	–0.013***	0.084
	(0.007)	(0.112)
Black	-0.106***	0.285
	(0.007)	(0.222)
Other races	-0.008	-0.065
	(0.008)	(0.118)
Unemployment rate	–1.343***	1.151
	(0.110)	(2.147)
Non-routine tasks	0.199***	0.443**
	(0.010)	(0.197)
R^2	0.426	0.468

*p <0.1; **p < 0.05; ***p < 0.01.

that the coefficient of computer-use wage return is higher for Washington State than that of the nation. The results suggest that multiple factors may lead to higher wages in Washington State. First, computer and Internet use brings wage premiums. A higher percentage of workers using computers in Washington State naturally lead to higher average wages.

Second, computer and Internet use wage return is higher in Washington State. Everything being equal, computer and Internet use brings higher wage returns in Washington State than the national level. It is likely the overall demand for skilled labor is higher in Washington State, which results in a higher wage premium for computer skills in the labor market.

Further, complementarities between computer and Internet use and nonroutine tasks may also contribute to higher wages. Regression results indicate that nonroutine task has a significant impact on wage return in Washington State. As workers use computers and information technologies in the workplace, jobs require higher level of problem solving skills and workers need to perform higher level of nonroutine tasks and take more responsibilities. The transformation in the workplace could be another important factor that leads to higher wages.

At an industry level, manufacturing, services, and agriculture sectors all lead the nation in terms of average wage and computer and Internet use at work (Table 7). The lead of manufacturing sector is especially significant. On average, about 38% of workers in the manufacturing sector use computers at work in the nation, compared to 58% in Washington State. Clearly, Washington State is more advanced in applying technologies in the manufacturing sector. On the other hand, financial services, construction, and wholesale and retail sectors in Washington State are trailing the nation in terms of computer and Internet use at work.

Table 7: Computer and Internet Use and Hourly Wage by Industry, 2001

Industry	Hourly Wage		Computer/Internet Use at Work (%)		Nonroutine Task (%)	
	Nation	Washington	Nation	Washington	Nation	Washington
Agriculture	10.36	12.47	12.75	18.75	45.4	42.5
Construction	16.40	18.83	16.98	16.67	41.9	40.4
Manufacturing	17.03	19.58	37.90	58.16	41.1	44.1
Transportation, communications, and utilities	17.72	16.57	39.12	40.68	52.8	54.7
Wholesale & Retail	11.92	12.75	23.19	22.11	47.6	47.6
Finance, insurance, & real estate	18.88	18.13	66.25	63.16	53.9	52.3
Services	16.49	17.61	46.00	51.98	54.7	56.1

5.2 Skill Requirements in the Workplace

Examining the components that contribute to nonroutine task scores in detail, we find that Washington State workers on average possess higher levels of skills on DCP and MATH (Table 5). As mentioned earlier, DCP measures workers' adaptability to accept responsibility for direction, control, and planning of an activity. DCP skills are critical to jobs that require negotiation, organization, supervising, and making final decisions.

MATH measures quantitative reasoning and analytical skills. The results suggest that Washington State workers tend to have higher managerial and analytical skills on direction, control, planning, and quantitative reasoning than the national average.

However, Washington State workers have lower scores on STS compared to the national average. STS score measures workers' ability to be precise and thorough in their jobs. STS skills are important for advanced technicians that operate complex machinery, measure and control industrial processes, and process data.

5.3 Disparities in Wage, Computer and Internet use, and Skill Requirements

We find significant disparities in terms of wage, computer and Internet use at work, and nonroutine scores, especially DCP and MATH, between metropolitan and non-metropolitan areas within the State.

First, average hourly wage in metropolitan areas is $17.30, almost 30% higher than the hourly wage of $13.40 in non-metropolitan areas in Washington State. Second, percentage of workers that use computers and the Internet at work in metropolitan areas is about 45%, compared to 33% in more rural areas. Further, workers in non-metropolitan areas lack behind job skill levels, especially in DCP and MATH.

At an industry level, financial services, manufacturing, and the general service sectors have a large percentage of workers using computers at work while the percentages are much lower in construction, agriculture, and wholesale and retail sectors.

5.4 Policy Implications

Although Washington State has a higher percentage of workers using computers and Internet at work than the nation, "digital divide" still exists today and it takes many forms. One important aspect of digital divide is the disparities of technology adoption between urban and rural areas. In addition, sectors such agriculture, construction, and wholesale and retail also lag behind in terms of computer and Internet use. Our study finds that computer and Internet use is a significant factor in contributing to wage returns. Therefore, in order to create high quality jobs in Washington State and promote economic development throughout the State, we have to address the gaps in terms of technology use between urban and rural areas, and between different industries.

Given the high importance of the agricultural sector in the Washington State, it is important to promote technology adoption in the rural areas and in the agricultural sector. Since population density is lower in many rural areas, computer and telecommunication technologies are perfect tools to help workers in rural areas to better communicate and link with suppliers, buyers and the markets. In addition, technologies can be used to enhance work productivity and help create new jobs. The following are specific policy implications:

Telecommunication infrastructure in rural areas. Many of today's computer applications rely on the telecommunication infrastructure. Therefore, Internet access and broadband networks are crucial in broadening computer and Internet use in rural areas. Private sector may lack incentives to offer such services in communities with lower population density. Government programs could provide incentives for private sectors to invest in telecommunication infrastructure in rural areas. In addition, government, communities, and industries can build partnership in adopting new technologies, such as WiMax, that are cost effective for providing broadband access in rural areas.

Use of generic computer tools. Our results suggest that generic computer tools are important in productivity gains and wage returns. Therefore, as we promote wider adoption of computer and Internet use and investments on telecommunication networks, it is important to train workers to learn basic productivity tools such as emails, word processor, and spreadsheets. Those tools are easy to use and can have significant impact on raising worker productivity. It is especially important to target the training in communities that have a large proportion of workers employed in agriculture, construction, and wholesale and retail sectors.

Training and Workforce Development. The findings of our study suggest that computer and Internet use is only one aspect of the productivity gain. The complementarity between technologies and advanced job skills are crucial in building a competitive and high-paying workforce. This requires partnership between businesses, education institutions such as community colleges and universities, and local communities. The focus should be on the use of technologies in the workplace and developing complementary job skills depending on the goal of the specific communities and industries.

High wage jobs in rural communities. There are enormous opportunities for rural Washington State in narrow the digital divide and create high quality and high wage jobs. With advanced communication and computer technologies, rural areas can create information-based jobs in rural communities. Such business opportunities range from call centers, billing and data processing centers, and server centers, which can take advantage of the low operation costs in rural areas. Successful examples include the Call Center 24x7 located in Port Angeles and a Microsoft server farm near East Wenetchee. Compared to offshore outsourcing, rural areas have the advantages of low operation risk and geographic proximity. To attract those jobs to rural Washington State, an important aspect is to develop workforce with necessary technology and complementary skills. Such job skills include communication, interaction, and data analysis. Our studies indicate workers in rural Washington State on average trail behind in those skills compared to urban areas in the State and the national average. Therefore, it is crucial to offer education and training programs that not only provide training on the use of computer tools but also help workers develop complementary communication, problem solving and analytical skills.

Use of technologies in traditional industries. Our results find high disparities in terms of computer and Internet use among industry sectors. Besides the agriculture sector, construction and wholesale and retail sectors also lag behind in using technologies in the State. This provides tremendous opportunities for those sectors to apply technologies to enhance worker productivity and make business more efficient. As discussed earlier, computer technologies are general purpose technologies and have the ability to spawn innovation and co-inventions regardless of the industrial sectors. It is conceivable that technologies could help better manage projects in the construction sector, and reduce inventories and costs in the wholesale and retail sector. Therefore, government programs and education institutions could develop training and education programs that specifically target those sectors in the State.

6. Conclusions

This study aims to explain how computers affect wage structures in the U.S. and analyze computer and Internet use and wage returns in Washington State. We find that the complementarity between computer and Internet use and non-routine tasks and the complementarity between computer and Internet use and workplace changes are major factors in explaining computer-use wage premium. The study provides an important extension of IT productivity research to the individual level. Ultimately, computers are used by humans, and any productivity gains by applying IT have to be realized through computer and Internet users. Understanding how computer and Internet use affects individual workers at task and skill level provides important insights on how computers complement workers, which helps organizations and managers to improve the design of business processes and job tasks. It is likely the changes in workplace require workers to take more responsibilities and to have new skills. Therefore, it is critical for companies to develop appropriate incentives and wage structures for the workers.

We also compare computer and Internet use and wage returns in Washington State with the national average. We find workers in Washington State on average use computers and Internet at a higher percentage than the national level and command a higher wage. However, there exist disparities in technology adoption between urban and rural areas in Washington State and among the state's various industries. The results provide important policy implications on promoting technology adoption and developing education and training programs in order to make Washington State workers more competitive.

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