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Does Computer and Internet Use Affect Employee Wage Premium? A Panel Analysis of CPS Data

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Abstract: This research investigates whether and to what extent the use of computers and the Internet at work affects employee wage premium. We construct a panel dataset from the 2000 and 2001 US Current Population Surveys (CPS) and apply fixed effects models to estimate the computer and Internet use wage premium. While cross-sectional analysis indicates a wage premium of about 14%, this premium drops to 3.4% after controlling for employee and employer heterogeneity within the panel analysis. In addition, our results show that the computer-use wage premium is highest for women employees who started to use computers and the Internet in the second year of the panel. The lower wage premium found in the panel analysis confirms the existence of omitted variable biases in cross-sectional analysis, but at the same time provides support that the estimated computer-use wage premium identified in prior studies cannot be purely attributed to unobserved employee heterogeneity.

Keywords: Computer and Internet use; Computer skills; Wage premium; Panel analysis

JEL Classifications: J21, J24, J31, J44

1. Introduction

Whether and to what extent employee wage levels are affected by work-related computer usage has attracted much attention of researchers for a long period of time. Using a US cross-sectional Current Population Survey (CPS) dataset for the years 1984 and 1989, Krueger (1993) found that employees who used computers at work were rewarded with 10 to 15% higher wages. However, later studies, such as DiNardo and Pischke (1997), Entorf and Kramarz (1997), and Entorf et al. (1999), argue that this wage premium may not be attributable to computer skills, and it may reflect the fact that higher-ability (and as a consequence better paid) employees simply happen to use computers at work. On the other hand, empirical evidence supporting the computer-use wage premium hypothesis is persistently found. For example, an earlier study by Bell (1996) revealed a significant wage return from computer usage after controlling for individual ability. Applying a fixed effects model, Dolton and Makepeace (2004) found a wage premium of about 9% for computer users, and Zoghi and Pabilonia (2007) confirmed the existence of a wage premium for work-related computer use. Significant return for computer use for employees has also been identified in DiMaggio and Bonikowski (2008).

In this study, we investigate this important question by providing new evidence of the computer-use wage premium. We use a novel approach to match employees included in the 2000 and 2001 CPS Computer and Internet Use Supplementary Surveys, and use their wage data to estimate the wage premium through panel data analysis. Since cross-sectional CPS data were used in Krueger's original study, we believe the results from a panel data analysis of the CPS data are particularly relevant in investigating the computer-use wage premium hypothesis.

The remainder of this paper proceeds as follows: Section 2 briefly reviews the literature, and identifies the research gap. Section 3 provides a detailed description of our datasets, the panel construction methodology, and the variable definitions. Various estimation models and results are presented in Section 4. Section 5 discusses the limitations of our study and concludes by offering future research directions.

2. Literature Review

The impact computer use has on wage premium has attracted increasing attention from researchers. The wide adoption and diffusion of computers and related technologies at workplace has increased the demand for skilled workers (Bound and Johnson 1992). Plenty of empirical studies have documented a robust correlation between increased use of computer-based technologies and increased demand for a skilled workforce (Bresnahan et al. 2002; Goldin and Katz 1998). At the same time, when employees use computers at their work, they tend to perform more efficiently and effectively, and wages, as a price for labor, would be expected to reflect this productivity gain (Lynch 1992). Indeed, early studies by Krueger (1993) and Bell (1996) identified significant wage returns for those using computers at work. Collectively, this stream of research suggests that the computer-use should command certain wage premium, and the computer-use wage premium hypothesis is theoretically sound and empirically supported.

Nevertheless, there exist counter-arguments and evidence as well. Probably the most serious detractor to the computer-use wage premium hypothesis was DiNardo and Pischke (1997). Using a German cross-sectional dataset, they replicated Krueger's study and found that measured wage differentials associated with work-related usage of pencils were of the same magnitude as those found for work-related usage of computers. Since they believed pencil use would not bring any lasting wage premium, they concluded that the computer-use wage premium found by past research might be spurious, and that employees' job-related abilities were the real driver of higher wages for computer usage: employees with higher abilities tend to be paid higher, and these employees also tend to use computers, as well as pencils, more often at work; thus the wage premium might simply reflect the fact that higher-ability (and therefore higher-paid) employees are using computers at workplace. However, these findings should not be interpreted as evidence against the existence of a causal relationship between computer use and wage premium. A computer is a very different tool from a pencil. Pencil use seldom impacts how a task is performed, but there are numerous studies and cases documenting the transformational role of computers in today's business and workplace (Autor et al. 2003; Levy and Murnane 1996). Indeed, the validity of DiNardo and Pischke's argument is called into question by Spitz-Oener (2008), who, using the same dataset but more recent years, found that the wage premium for using pencils disappears over time while that for using computers remains robust.

In addition to the studies mentioned above, a few other studies have also identified positive returns to computer and Internet use (DiMaggio and Bonikowski 2008; Dolton and Pelkonen 2008; Lee and Kim 2004; Liu et al. 2004; Peng and Eunni 2011). However, these studies all used cross-sectional analysis, which may lead to biased estimates for the computer-use wage premium.

We believe that, to better frame the analysis over the existence and the magnitude of a computer-use wage premium, research design flaws, such as potential omitted variable bias in ordinary least squares (OLS) models and the possibility of upwardly biased wage premium accompanying cross-sectional analyses, need to be carefully examined and remedied. One possible and highly encouraged approach is to adopt panel analysis when estimating the wage premium (Di Pietro 2007; DiNardo and Pischke 1997; Pabilonia and Zoghi 2005).

However, most current studies that have adopted panel analysis only emphasize the importance of controlling for employee heterogeneity such as individual ability, and few have paid attention to employer heterogeneity (Dolton and Makepeace 2004; Entorf et al. 1999; Zoghi and Pabilonia 2007). Firms differ significantly in their management practices and wage policies. Better managed firms may invest more in computer equipment, and thus have a higher demand for computer skills (Black and Lynch 2001; Bresnahan et al. 2002; Brynjolfsson and Hitt 2003). Thus, it is well possible that employees are paid higher simply because they take positions with better managed employers. An important implication is that when panel analysis is adopted to estimate the computer-use premium, it is equally important to control for employer heterogeneity, in addition to employee heterogeneity. We address these issues in this study.

3. Data and Methodology

3.1 Data

The data used in this study come from the Current Population Surveys (CPS) administered by the US Census Bureau and the US Bureau of Labor Statistics. The CPS Surveys have been conducted for more than 60 years. They constitute the primary source of official government statistics for the US labor force, and provide a rich dataset for researchers and policymakers to evaluate and plan government programs (Autor et al. 2003; Krueger 1993). Currently there are about 60,000 households surveyed each month as part of the basic monthly surveys. Respondents are asked about the employment status of each member of the household who is 16 years of age or older. In addition, a variety of other statistics including earnings, hours of work, and demographic characteristics are collected. The supplementary surveys are designed to meet a variety of additional needs and are primarily used to gather in-depth information on specific aspects of the labor force. During August 2000 and September 2001, two supplementary surveys focusing on computer and Internet usage were conducted. We used the following two questions from the two surveys to measure whether an individual used both a computer and the Internet at work in each of the two years: 1) "*Where does (the person) use the Internet? Does (he/she) use it at work?*" from the 2000 survey, and 2) "*At work, does (the person) use the computer to connect to the Internet or use e-mail?*" from the 2001 survey. Although the above questions are worded slightly different in the two surveys, they should measure the same item—whether or not the individual uses both a computer and the Internet at work.

In addition, in both years, the surveys also asked whether the individual used the Internet at home. In Table 1, we list the percentages of *computer and Internet users at work* and *Internet users at home* for major occupation groups and industry sectors based on the results of the two surveys. It shows that both percentages increased consistently over the two years for all occupation groups and industry sectors.

Table 1. Percentages of computer and internet users at work and at home

Categories	Computer and Internet Users at Work (%)		Internet Users at Home (%)	
	Year 2000	Year 2001	Year 2000	Year 2001
Occupation Groups				
Managerial	49.4	70.9	60.2	67.4
Professional	47.4	65.6	65.9	72.9
Technician	35.3	52.7	56.2	65.0
Sales	21.4	37.0	48.2	57.2
Clerical	26.8	49.6	46.1	55.2
Private household	4.6	4.8	26.1	33.9
Protective	20.0	33.9	46.1	53.7
Other service	3.7	8.3	28.6	37.2
Precision production	11.0	18.5	40.0	41.4
Machine operators	4.7	10.4	28.0	31.6
Transportation	4.7	6.0	24.9	28.8
Laborers	3.1	6.8	28.2	33.5
Farming, forestry, and fishing	5.3	9.9	22.5	33.3
Industry Sectors				
Agriculture, forestry, and fisheries	10.6	18.2	27.4	35.8
Mining	19.1	29.0	40.2	47.2
Construction	10.5	16.7	30.2	37.9
Manufacturing	23.7	37.2	39.2	48.5
Transportation, communications, and utilities	23.8	38.8	45.4	53.0
Wholesale and retail trade	13.0	23.4	41.5	50.0
Finance, insurance, and real estate	41.3	65.7	53.5	60.5
Service industry	32.6	48.2	51.6	59.4
Public administration	39.7	60.6	51.7	60.4

***Note*:** N=43,675 in year 2000 and 51,891 in year 2001.

3.2 Construction of the Panel Dataset

CPS uses 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). The whole sample is divided into eight representative subgroups called rotation groups. Households in each rotation group are interviewed for four consecutive months, followed by an eight-month break, and then another four months of interview. After that, the households leave the CPS sample permanently. In a given month, about one-eighth of the households are interviewed for the first time, while one-eighth leaves the sample temporarily, and another one-eighth leaves the sample permanently. The two subgroups leaving the sample are called outgoing rotation groups (Madrian and Lefgren 2000). To control for migration, a third variable, HHNUM, is used. It is initialized at one and is incremented by one every time a new family moves into the same household address.

In this study, we make use of the 2000 and 2001 Computer and Internet Use Supplementary Surveys to construct a two-year panel dataset. Two rounds of matching were used to construct the panel.

Because wage data are available only for employees in the outgoing rotation groups and we wanted to maximize our sample size, we first matched employees from August 2000 supplementary survey to those from basic monthly surveys in the three following months, i.e., September, October, and November for year 2000. For all employees surveyed in the first month, about 75% of these can be matched in the following month, 50% in the next succeeding month, and 25% in the last month (Madrian and Lefgren 2000). This is illustrated in Figure 1 by the four columns to the left. The same matching process was applied to September 2001 Supplementary Survey: employees in September 2001 Supplementary Survey were matched to those from October, November, and December 2001 basic monthly surveys to obtain more wage data.

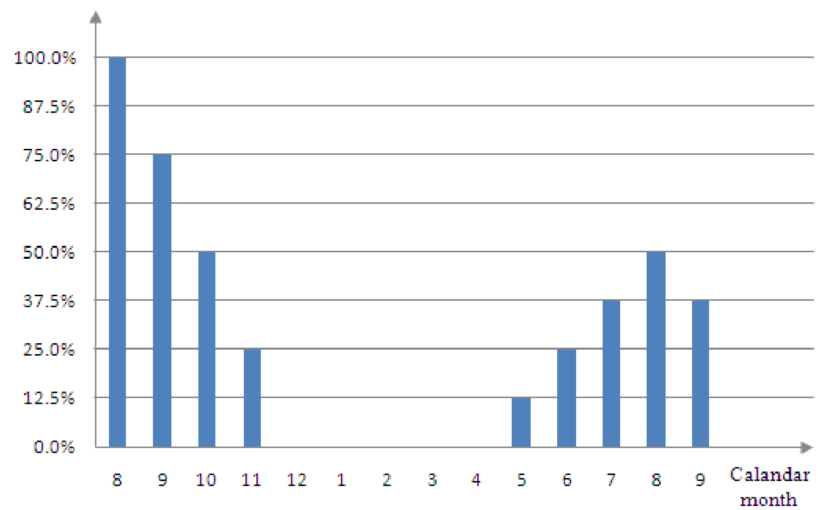

Figure 1. Percentages of matched employees over months

To ensure that the wages obtained from the basic monthly surveys in the succeeding months reflected the wages for doing the same work identified in the two supplementary surveys, we made use of two other questions in the basic surveys: 1) "*do you still work for the same employer?*" and 2) "*have the usual activities and duties of your job changed?*" As part of the wage matching process, we included in our sample only those employees who answered "yes" to the first question and "No" to the second question.

The second round of matching comes in when constructing the two-year panel. With the availability of all the data, this is straightforward. Theoretically, a unique triple (HHID, LineNo, and HHNUM) as discussed earlier should be sufficient to match the same employees included in the two supplementary surveys (Madrian and Lefgren 2000). To further ensure matching quality, we add gender, race, region, and metropolitan area into the matching criteria, because these variables should not change for an employee over the two years. As discussed earlier, employer heterogeneity can bias the wage premium estimated from OLS models. To avoid this type of bias, we further limited the sample to those employees who remained with the same employer over the two years. To assure that this was the case, we made use of the employee's answer to the 2001 Computer and

Internet Use Supplementary Survey question "*do you still work for the same employer?*" We only retained those employees who answered "yes" to this question and matched employees with the year 2000 data. This way we can take care of the employer heterogeneity when conducting panel analysis. As shown in Figure 1 (the last column to the right), since the two surveys are 13 months apart, about 37.5% of the employees can be matched across years. This finally leaves us with a sample of 10,196 employees for the two-year panel dataset used in this study.

3.3 Variables

In order to be consistent with previous research and theory, we used log hourly wage as the dependent variable (Mincer 1974). Wage determinants are mainly drawn from three strands of theory: human capital theory, compensating wage differentials theory, and labor market discrimination theory (Rosen 1986). Following these theories, we gathered employee specific data from the CPS surveys so that we can control for employee differences in education (in years), work experience (in years), gender, marital status, union status, employment type (full-time or part-time), location (living in a metropolitan area or not), veteran status, and race, etc.

Table 2. Descriptive statistics (means and standard deviations)

Variables	Year 2000	Year 2001	Year 2000 (Panel)	Year 2001 (Panel)
Log wage	2.556 (0.519)	2.599 (0.516)	2.610 (0.503)	2.636 (0.502)
Computer and Internet use at work	0.249 (0.432)	0.393 (0.488)	0.271 (0.444)	0.422 (0.494)
Education	13.552 (2.753)	13.641 (2.717)	13.672 (2.704)	13.729 (2.694)
Experience	19.878 (12.847)	20.219 (12.807)	21.498 (11.990)	22.473 (12.055)
Male	0.510 (0.500)	0.504 (0.500)	0.506 (0.500)	0.506 (0.500)
Married	0.736 (0.441)	0.742 (0.438)	0.802 (0.398)	0.806 (0.395)
Union member	0.142 (0.349)	0.145 (0.352)	0.169 (0.375)	0.171 (0.376)
Full-time	0.842 (0.365)	0.825 (0.380)	0.876 (0.330)	0.871 (0.336)
Living in a metropolitan area	0.780 (0.414)	0.764 (0.425)	0.766 (0.423)	0.766 (0.423)
Veteran	0.099 (0.299)	0.098 (0.297)	0.105 (0.307)	0.106 (0.308)
Black	0.095 (0.293)	0.092 (0.288)	0.083 (0.276)	0.083 (0.276)
Other races	0.052 (0.222)	0.051 (0.220)	0.045 (0.208)	0.045 (0.208)

***Notes*:** N=43,675 in year 2000 and 51,891 in year 2001 for the unmatched samples, and N=10,196 in the matched panel; the means and standard deviations are listed under each year.

In the individual earning function, log wage is found to be concave on work experience; thus, experience takes a quadratic form in the function (Mincer 1974). As discussed earlier, computer and

Internet use variables are available directly from the two supplementary surveys. We view computer and Internet use at work as a proxy for computer knowledge and IT skills (DiNardo and Pischke 1997) and interpret the results this way subsequently.

The descriptive statistics of the unmatched samples from year 2000 and 2001 supplementary surveys, as well as those of the matched panel, are shown in Table 2. It can be observed that compared with employees from the two surveys, employees from the matched panel have higher levels of education and work experience, indicating that abler employees might be over-represented in the panel. As a result, returns to unobservable employee heterogeneity tend to be higher in our matched panel, potentially causing lower return to using a computer and Internet at work. Put it another way, our panel construction method could potentially introduce a downward bias, rather than an upward bias, in the estimated return to compute and Internet use.

4. Estimation Results

For comparison, we first estimated the following OLS model for year 2000 and 2001 separately:

$$Y_i = \mathbf{X}_i{}'\boldsymbol{\gamma} + \theta I_i + \varepsilon_i \tag{1}$$

where Y_i is log hourly wage, $\mathbf{X}_i$ is a vector of wage determinants, I_i is a dummy variable for computer and Internet use at work, and ε_i is random error. We set I_i =1 if employee i uses a computer and the Internet at work in the years 2000 and 2001, and 0 otherwise. The OLS results of Equation (1) are reported in the first two columns of Table 3. They show, in aggregate, a higher return for using a computer and Internet at work in both year 2000 and 2001—about 12% and 14% respectively.[1] This is consistent with the results of Krueger (1993).

Next we estimated the following fixed effects model:

$$Y_{it} = \alpha_i + \beta_i + \mathbf{X}_{it}{}'\boldsymbol{\gamma} + \theta I_{it} + \varepsilon_{it} \tag{2}$$

where $t = \{2000, 2001\}$, α_i is the employee heterogeneity, and β_i is the employer heterogeneity. As shown in the third column of Table 3, the estimated wage premium drops sharply to 3.4% in the fixed effects model.[2] This result is comparable to that found by Zoghi and Pabilonia (2007).

The sharp drop of wage premium from the OLS to the fixed effects model confirms that, in the original study of Krueger (1993), a large portion of the computer-use wage return may well has been caused by unobserved heterogeneity, such as differences in employee ability and employer specific factors. The real question, of course, is whether the whole wage return can be attributed to unobserved heterogeneity, as has been implied or suggested by DiNardo and Pischke (1997). We believe this is not likely for three reasons. First, the fixed effects results in Table 3 show a small but highly significant return to computer and Internet use. Second, as mentioned earlier, our panel construction method may introduce a downward bias, rather than an upward bias for the wage premium. Third, the fixed effects results may also underestimate the returns to computer and Internet use because wages tend to be downwardly rigid. Such rigidity would limit wage reductions that might otherwise occur when an employee no longer uses a computer and the Internet (Pabilonia

[1] The computer and Internet use premium is calculated as $e^{0.114} - 1 = 0.121$ and $e^{0.131} - 1 = 0.140$.

[2] The premium is calculated as $e^{0.033} - 1 = 0.034$.

and Zoghi 2005), thus dampening the impact of computer use on wages. Because of these reasons, we believe the 3.4% wage premium found within the fixed effects model represents a lower bound of the wage premium for computer and Internet use by our sample.

Table 3. Estimated results for equations (1) and (2)

Dependent variable: ln(Wage)	**2000 (OLS)**	**2001 (OLS)**	**2000-2001 (Fixed Effects)**
Computer and Internet use at work	0.114** (0.009)	0.131** (0.009)	0.033** (0.008)
Education	0.052** (0.002)	0.051** (0.002)	0.051** (0.005)
Experience	0.018** (0.001)	0.018** (0.001)	0.029** (0.007)
Experience^2/100	–0.029** (0.003)	–0.031** (0.002)	–0.025* (0.012)
Male	0.191** (0.008)	0.183** (0.008)	_____
Married	0.081** (0.011)	0.093** (0.011)	0.007 (0.029)
Union member	0.131** (0.010)	0.110** (0.010)	0.061** (0.013)
Full-time	0.171** (0.012)	0.136** (0.009)	0.075** (0.014)
Living in a metropolitan area	0.122** (0.009)	0.138** (0.009)	_____
Veteran	0.012 (0.013)	–0.002 (0.013)	–0.116** (0.043)
Black	–0.080** (0.013)	–0.092** (0.014)	_____
Other races	–0.024 (0.017)	–0.018 (0.017)	_____
R^2	0.481	0.463	0.420
ρ	_____	_____	0.680

***Notes*:** N=10,196; **p<0.01, *p<0.05; estimated coefficients and their standard errors are listed under each model. White is the base race group.

Although the traditional fixed effects model can take care of employee and employer heterogeneity, it is too restrictive in a sense that θ is assumed to be the same over the two years. However, this might not be the case since the computer wage premium, if any, might be competed away overtime. If we are willing to relax this assumption, we then have:

$$Y_{it} = \alpha_i + \beta_i + \mathbf{X}_{it}'\boldsymbol{\gamma} + \theta_t I_{it} + \varepsilon_{it} \tag{3}$$

or $Y_{i1} = \alpha_i + \beta_i + \mathbf{X}_{i1}'\boldsymbol{\gamma} + \theta_1 I_{i1} + \varepsilon_{i1}$ and $Y_{i2} = \alpha_i + \beta_i + \mathbf{X}_{i2}'\boldsymbol{\gamma} + \theta_2 I_{i2} + \varepsilon_{i2}$, where θ_1 and θ_2 are returns to computer and Internet use in years 2000 and 2001 respectively. Taking the difference between these two time periods yields:

$$Y_{i2} - Y_{i1} = (\mathbf{X}_{i2} - \mathbf{X}_{i1})'\boldsymbol{\gamma} + \theta_2 I_{i2} - \theta_1 I_{i1} + (\varepsilon_{i2} - \varepsilon_{i1}) \tag{4}$$

Therefore, θ_1 and θ_2 can be estimated directly through Equation (4) using a standard OLS model. The OLS results found using Equation (4) are reported in Table 4.

Table 4. Estimation results for equation (4)

Coefficients	**All** (*N*=10,196)	**Men** (*N*=5,159)	**Women** (*N*=5,037)
θ_1	0.032** (0.010)	0.034* (0.015)	0.033** (0.013)
θ_2	0.032* (0.009)	0.031* (0.013)	0.032** (0.012)

***Note*:** ***p*<0.01; **p*<0.05.

The first column in Table 4 shows that θ_1 and θ_2 are both positive and significant, indicating that the use of computers and the Internet had a positive and significant impact on wage returns in both 2000 and 2001. Table 4 also shows the results separately for men and women. The results suggest that this wage return is of similar magnitude for both men and women in both years.

Table 5. Four groups of employees and their statistics

	Stayers	**Enterers**	**Leavers**	**Laggards**
All (*N*=10,196)	2,117	2,183	642	5,254
Men (*N*=5,289)	1,002	962	315	2,880
Women (*N*=5,054)	1,115	1,221	327	2,374
Education†	15.6	14.5	14.4	12.6
Age†	42.5	42.5	42.5	42.0
Experience†	21.0	22.0	22.0	23.3
Fulltime (%)†	94.7	90.7	90.5	82.0
Same jobs	1,543	1,476	431	3,702
Different jobs	574	707	211	1,552

***Note*:** †based on year 2001 data in the matched panel.

Although Equation (4) takes into consideration the possibility that the wage returns across the two periods might differ, it does not take into consideration that the returns may also vary across different computer usage groups. To determine if this indeed was the case, we sort each employee i in the matched panel into one of the following four groups based on computer and Internet usage status: 1) used a computer and Internet in both years (*stayers*), 2) did not use a computer and Internet in 2000 but started to use in 2001 (*enterers*), 3) used a computer and Internet in 2000 but stopped using them in 2001 (*leavers*), and 4) remained not using a computer and Internet over the two years (*laggards*).

Table 5 summarizes the distribution of the 10,196 employees among these four groups, and also provides added descriptors for the employees in each of these groups.

Several apparent patterns are observed: *i*) men and women are similarly distributed among the four groups of employees, *ii*) stayers have the highest education and the highest percentage of full-time employment. In contrast, the laggards have the lowest education and the lowest percentage of full-time employment, *iii*) all groups have similar ages and work experience, and *iv*) the stayers is the group least likely to have changed their jobs across the two years.

As indicated above, Equation (3) assumes the same return, θ, to all four groups of employees in the same year. However, this might not be true. If we are willing to relax this, Equation (3) can be further expanded to include group heterogeneity:

$$Y_{it} = \alpha_i + \beta_i + \mathbf{X}_{it}'\boldsymbol{\gamma} + \theta_t^S Stayer_i + \theta_t^E Enterer_i + \theta_t^L Leaver_i + \varepsilon_{it} \tag{5}$$

where the group of laggards is the base group. Taking the difference between the two periods and considering the fact that $\theta_1^E = \theta_2^L = 0$, we have:

$$Y_{i2} - Y_{i1} = (\mathbf{X}_{i2} - \mathbf{X}_{i1})'\boldsymbol{\gamma} + (\theta_2^S - \theta_1^S)Stayer_i + \theta_2^E Enterer_i - \theta_1^L Leaver_i + (\varepsilon_{i2} - \varepsilon_{i1}) \tag{6}$$

The OLS results from Equation (6) are reported in the first column of Table 6.

Table 6. Estimation results for equation (6)

	All (*N*=10,196)	**Men** (*N*=5,159)	**Women** (*N*=5,037)
Stayers ($\theta_2^S - \theta_1^S$)	−0.003 (0.010)	−0.005 (0.015)	−0.003 (0.014)
Enterers (θ_2^E)	0.038** (0.010)	0.035* (0.015)	0.040** (0.013)
Leavers (θ_1^L)	0.016 (0.017)	0.023 (0.024)	0.011 (0.023)

***Notes*:** *N*=10,196; ***p*<0.01, **p*<0.05; Base group is laggards.

It shows that $\theta_2^S - \theta_1^S$ is not significant, suggesting that there is no significant difference in the wage premium for those who used a computer and Internet in both 2000 and 2001. θ_2^E is positive and significant, suggesting that employees who started to use a computer and the Internet in the second year witnessed a significant wage increase. Finally, θ_1^L is positive but not significant, indicating that those employees who discontinued their use of the computer and the Internet in the second year did not incur significant wage losses. We believe that downward wage rigidity may well explain why leavers did not incur significant wage losses in the second year. Such wage rigidity would make it difficult to cut back wages even after employees stopped using computers (Pabilonia and Zoghi 2005).

We also estimated Equation (6) for men and women respectively. The results in Table 6 show similar patterns: for both men and women, it is the *enterers* (those employees who started to use a computer and Internet in the second year), who commanded the highest wage premiums across years. In particular, this wage premium is about 4.1% for women enterers.[3]

5. Discussions and Conclusions

Since the work of DiNardo and Pischke (1997), it has been widely believed that earlier findings of a computer-use wage premium merely represent a correlation between computer use and wage return. In this paper, we argue their findings should be interpreted judiciously, and indeed computer use at work can potentially lead to a wage premium. To support our argument, we construct a panel dataset from year 2000 and 2001 CPS Computer Supplementary Surveys to estimate the wage premium. We find a wage premium of around 14% in our cross-sectional analysis. This premium is of the same magnitude as that found in Krueger (1993). However, the estimated premium decreases to 3.4% after controlling for employee and employer heterogeneity in the fixed effects model. We further estimate this premium over different time periods and based on different groups of employees, and found that the wage premium for women who started to use a computer and Internet in the second year is the highest, about 4.1%. Taken together, the results suggest that while the criticism on omitted variable bias from prior studies is justifiable, the assertion that the computer-use wage premium can be purely attributed to unobserved individual heterogeneity is most likely over-stated, at least during our study periods.

We are also aware of the limitations of the study. First, the CPS data miss some crucial information about seniority in the specification of the wage equation, such as experience with computers, which are predicted to affect the computer-use wage premium (Entorf et al. 1999). Second, there are possible measurement errors, which could affect the results of this study. For example, the CPS questions were answered by the householder on behalf of all household members, and this will almost certainly bring in measurement errors. Despite these limitations, we believe our study contributes to the understanding of how computer use and computer skills have affected wage premium and worker compensation in general.

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