The impact of computer use on wages in a developing country: Evidence from Ecuador[1]

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Abstract

This paper examines the wage premium to computer use in a developing country: Ecuador. We use different approaches to examine whether the premium is causal. Controlling for an extensive set of observables, we find a wage difference between users and non-users of around 20%. Using first differences, the premium drops and is no longer significant in a specification that includes proxies for workers' computer experience and knowledge. Estimates of the impact of the intensity of computer use are also small and in most cases insignificant. Estimates of the pencil premium are substantial in level specifications, but become insignificant in fixed effect specifications. Taken together, the findings suggest that also in the setting of a developing country the computer premium does not reflect a causal impact of computers on productivity, but should be attributed to unobserved worker and/or job characteristics.

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1 Introduction

The sharp increase in wage inequality during the past decades has generated a debate about its causes. Skill bias technological change is one of the proposed explanations. As evidence in support of this explanation, various studies show that employees who use computers in their workplace earn higher wages than employees who do not use computers.[1]

There is a fair amount of controversy, however, as to whether this "computer premium" really reflects an increase in workers' productivity. Using data from Germany, DiNardo and Pischke (1997) find that using calculators, telephones, pens or pencils at work also has a positive effect on wages. Using data for Canada, Drolet and Morissette (1998) show that using fax machines is associated with higher earnings, even yielding a higher premium than computers. For the Netherlands, Oosterbeek (1997) finds that returns to computer use do not vary with the intensity of it, which can be seen as evidence against the productivity interpretation. Using longitudinal data for France, Entorf et al. (1999) find that workers who use a computer were already better compensated than non-users before the introduction of personal computers. On the other hand, they also report positive effects of computer experience that never exceed 2%, which is far below the cross-section estimates. This latter result supports the productivity argument.

High returns to computer use can only be causal if there is a shortage of computers and/or of the skills to use them. Otherwise, each worker would be equipped with a computer thereby raising their productivity. A shortage of computers or of the skills to operate them is not very realistic in the developed countries for which the results mentioned above were obtained. A shortage of computers or the skills to use them is more likely in the context of developing countries. The evidence on the impact of computers on wages in developing countries is however thin.

For Korea, Choi (1993) shows that workers are paid more in industries where technology changes rapidly than in industries where technology changes slowly. In Mexico, Taiwan, Colombia, and Malaysia, Tan and Batra (1995, 1997) find that workers are more likely to get training when the rate of technological change is high and are paid a wage premium. Firms' investments in technology lead to large wage premiums for skilled workers but not for unskilled workers. Sakellariou (2002) finds that sustained high returns to education over time are the result of increasing

[1] See for instance: Krueger (1993) for the United States, Miller and Mulvey (1997) and Chiswick and Miller (2007) for Australia, Reilly (1995) for Canada, and Arabsheibani et al. (2004) for the United Kingdom. See Sakellariou and Patrinos (2004) for an overview of more estimates of the computer premium.

demand for highly skilled graduates in Singapore. Sakellariou and Patrinos (2000, 2004) report that earnings increase by 10 to 14 percent among tertiary education graduates in Vietnam if the hold a job that requires computer skills. In a later study using the same data Sakellariou (2009) confirms this finding using an instrumental variable approach.

This paper reports new evidence of the computer premium in the context of a developing country: Ecuador. Ecuador is a lower-middle income country, characterized by high poverty levels and high inequality.[2] We collected longitudinal data about workers' computer use and their wages. In addition we collected information concerning the intensity of computer use and the use of other desk materials at work. This information allows us to estimate the computer premium using first differences, and to compare these findings with the impacts of the intensity of computer use and the use of other desk materials. We find a substantial computer premium in the cross-section estimates and also in some fixed effects specifications. The computer premium is, however, no longer statistically significant in the most extensive fixed effects specification. Our findings for the impacts of the intensity of computer use and the use of other desk materials are consistent with this. Taken together the results suggest that the computer premium in Ecuador is not due to an increase in productivity.

The remainder of this paper is organized as follows. Section 2 describes the data and presents descriptive statistics. Section 3 discusses our empirical approach. Section 4 presents and discusses the results, and section 5 summarizes and concludes.

2 Data and descriptive statistics

The data come from household surveys that were collected by the Latin America Faculty of Social Sciences in Ecuador. The baseline survey was collected in March 2006, and the follow-up in May 2007. The parts of the surveys that we use in our analyses have the structure of conventional labor force surveys and include information on individual earnings, lab our conditions, years of education and years of experience. In addition the questionnaires include a separate module with specific questions about the use of computers.

Data collection was based on a rotating panel design implying that only $\frac{2}{3}$ of the baseline sample was re-interviewed in the follow-up survey. Table 1 shows by year the numbers of observations that satisfy certain conditions to be included in the final samples that we use in the analyses. Starting from total sample sizes of

[2]In 2008, 64 percent of the urban population lived below the national poverty line. In 2009, the Gini coefficient of family income was equal to 0.48.

Table 1. Numbers of observations, by year

	Baseline 2006	Follow-up 2007
All	9136	9087
Working age (15<age<65)	7431	7485
Active	4231	4237
Employed	3825	3891
Reports wage	2848	3410
No further missings: In cross-section	2621	3298
In panel	1717	1717

Note: Requirements are cumulative from top to bottom; e.g. in 2006, 4231 observations are working age *and* active.

over 9000 observations, we end up with around 3000 observations that can be used in cross-sectional analyses, and with 1717 observations that can be used in panel data analyses. Slightly under 2000 observations are lost since they do not fulfill the age condition. Another 3200 observations is excluded each year because they are not part of the active labor force. Around 400 observations are lost because they are unemployed, and another 400 observations do not report wages. Finally we loose around 200 observations in each year due to missing values on some important control variables.

Table 2 shows how the various steps towards inclusion in the cross-section data set of 2006 is related to respondents' background characteristics.[3] The first column shows that being active in the labor market is positively associated with years of schooling and household size and negatively with being female, being married and living in Guayaquil (instead of Quito or Cuenca). The relationship with age follows an inverse u-shape; until the age of 45 the probability of being active increases with age, after 45 it decreases with age. The second column shows the relationship between being employed (conditional on being active) and background characteristics. Again we observe an inverse u-shape relationship with age; now the maximum is reached at the age of 58. The conditional probability of being employed is lower for women than for men, and is also lower for citizens of Quito and Guayaquil than for citizens of Cuenca.

Reporting the wage (conditional on being employed) is affected by years of education, age (increasing till age 38, decreasing after), gender, household size, and city (see the third column). The final column shows that missing values on other variables are only related to city, with fewer cases from Quito and Guayaquil dropped

[3]Results are very similar when we use data for 2007.

Table 2. Determinants of selection into the cross-section sample of 2006

	Active	Employed	Reports wage	No further missings
Years of education/100	0.519***	0.018	-0.616***	-0.062
	(0.093)	(0.075)	(0.118)	(0.062)
Age	0.061***	0.015***	0.014***	0.003
	(0.001)	(0.002)	(0.003)	(0.002)
Age squared/1000	-0.674***	-0.129***	-0.185***	-0.015
	(0.017)	(0.020)	(0.036)	(0.017)
Female	-0.219***	-0.101***	-0.054***	0.014
	(0.010)	(0.011)	(0.016)	(0.009)
Married	-0.037***	-0.001	-0.021	-0.000
	(0.013)	(0.012)	(0.017)	(0.010)
Household size	0.012***	-0.002	-0.026***	-0.004
	(0.003)	(0.003)	(0.005)	(0.004)
Quito	0.006	-0.053***	0.053***	0.119***
	(0.013)	(0.011)	(0.017)	(0.015)
Guayaquil	-0.044***	-0.073***	-0.174***	0.112***
	(0.013)	(0.011)	(0.019)	(0.016)
N	7376	4191	3785	2821
R^2	0.354	0.074	0.081	0.031

Note: estimates from linear probability models that also include a constant term. Robust standard errors in parentheses. * indicates significance at the 10%-level; ** indicates significance at the 5%-level; *** indicates significance at the 1%-level.

from the sample for this reason. The patterns reported in Table 2 create sample selection issues that might bias the estimates of the computer and pencil premiums. With the available data, there is no clear-cut approach to correct for this potential bias. In addition to the OLS-regressions reported in Section 4, we also estimated Heckman selection models in which the explanatory background variables of Table 2 are included in the selection equations. In this approach, the correction is based on functional form assumptions. The results obtained using this approach, are virtually identical to the results reported in Section 4.

Before we analyze selectivity due to attrition, Table 3 reports descriptive statistics for the variables used in the analyses. Statistics are presented for the cross-section samples of 2006 and 2007, separately for computer users and non-computer users. In both years, computer users have higher average wages than non-computer users. Wages are defined as earnings from paid work per period (week or month) divided by the number of actual working hours during that period. On average, computer users use their computer at work during around 23 hours per week. Computer users are also more likely to use other desk materials (from now on we will refer to other desk materials as "pencils") than non-computer users.

Computer users have on average almost twice as many years of education, are around 3.5 years younger, are relatively more often female and less often married than non-computer users. The firms where computer users work more often belong to the modern sector, to the formal sector, to the public sector, have social security coverage and are larger than the firms that where non-computer users work. Also the jobs that computer users hold differ from those of non-computer users: in terms of training, and in type of position (staff, permanent, managerial, salary earner). Finally, in both years, computer users possess more computer experience than the non-users. More often they have a job as computer programmer, have a computer at home and claim that they know how to operate a computer. In the period covered by the two waves, the share of people that use a computer at work increased from 20 percent to 21 percent, with a light decrease in the number of hours per week spent using a computer (intensity). The fraction of people that claim to know how to use a computer increased slightly. The data set includes sample weights, and using them makes the sample representative for the three main cities of the country: Quito (the capital), Guayaquil and Cuenca.

We will present analyses based on annual cross-sections as well as on panel data from individuals who are observed in both years. Presenting only results based on individuals that are observed in both years would give a biased picture if attrition from the data set is partially selective. Table 4 shows results from linear probability models in which we regress attrition on various explanatory variables. The dummy for attrition equals one for individuals that are observed in 2006 but not in 2007 and zero for individuals that are observed in 2006 and also in 2007. The results show that attrition from the sample is strongly related to age, household size and some sector dummies. The age pattern is u-shaped and reaches a minimum at age 40. This means that younger workers and older workers are more likely to dropout from the sample. For young workers this might be due to them leaving the household of their parents. For older workers this might be due to reaching retirement age. People belonging to larger households are also more likely to leave the sample. The obvious explanation is that those who are not the household head in the 2006 survey may have started their own household. Being employed in the modern sector or in the informal sector reduces the probability to drop out from the sample. The most important result in Table 4 is, however, that attrition is unrelated to using a computer at baseline, and is also not related to using a pencil at baseline and the (log) wage rate at baseline.

Table 3. Descriptive statistics, by computer use and year

	Baseline (2006)			Follow-up (2007)		
Variable	Non-user	User	p	Non-user	User	p
Log hourly wage	1.50	2.19	0.00	1.49	2.09	0.00
Intensity of computer use (hrs/wk)	0.00	24.0	0.00	0.00	22.3	0.00
Pencil (dummy)	0.02	0.73	0.00	0.03	0.73	0.00
Background:						
Years of education	9.7	18.0	0.00	10.0	18.1	0.00
Age (in years)	39.2	35.7	0.00	39.5	36.1	0.00
Female (dummy)	0.38	0.45	0.01	0.37	0.46	0.00
Married (dummy)	0.66	0.52	0.00	0.64	0.52	0.00
Household size (persons)	1.65	1.57	0.22	1.01	1.01	0.99
Quito (dummy)	0.45	0.50	0.03	0.40	0.41	0.48
Guayaquil (dummy)	0.35	0.28	0.00	0.40	0.34	0.01
Firm:						
Modern sector (dummy)	0.36	0.87	0.00	0.38	0.87	0.00
Informal sector (dummy)	0.55	0.13	0.00	0.53	0.13	0.00
Social security (dummy)	0.21	0.58	0.00	0.21	0.62	0.00
Firm size (persons)	19.7	50.4	0.00	19.4	48.9	0.00
Public sector (dummy)	0.06	0.20	0.00	0.06	0.17	0.00
Job:						
Training (dummy)	0.03	0.23	0.00	0.04	0.19	0.00
Job tenure (months)	104.5	95.2	0.07	98.6	95.9	0.54
Staff position (dummy)	0.05	0.19	0.00	0.05	0.15	0.00
Permanent position (dummy)	0.31	0.53	0.00	0.28	0.58	0.00
Managerial position (dummy)	0.05	0.08	0.02	0.04	0.07	0.02
Self-employed (dummy)	0.37	0.10	0.00	0.38	0.08	0.00
Salary-earner (dummy)	0.50	0.82	0.00	0.50	0.85	0.00
Computer experience:						
Programmer (dummy)	0.01	0.17	0.00	0.01	0.14	0.00
Computer knowledge (dummy)	0.23	1.00	0.00	0.25	1.00	0.00
Computer at home (dummy)	0.07	0.60	0.00	0.07	0.50	0.00
N	2098	523		2603	695	

Note: p-values are based on t-tests for the difference between users and non-users.

Table 4. Determinants of attrition from the sample between 2006 and 2007

	(1)	(2)	(3)	(4)
Computer	-0.001	0.010	0.015	0.011
	(0.028)	(0.029)	(0.030)	(0.031)
Pencil	0.010	0.021	0.029	0.028
	(0.029)	(0.031)	(0.032)	(0.032)
Log hourly wage	0.008	0.011	0.016	0.016
	(0.012)	(0.012)	(0.013)	(0.013)
Years of education	0.002	0.002	0.003	0.003
	(0.002)	(0.002)	(0.002)	(0.002)
Age	-0.017***	-0.017***	-0.016***	-0.016***
	(0.003)	(0.003)	(0.004)	(0.004)
Age squared/1000	0.212***	0.213***	0.211***	0.210***
	(0.039)	(0.039)	(0.042)	(0.042)
Female	0.024	0.023	0.021	0.022
	(0.017)	(0.018)	(0.019)	(0.019)
Married	-0.022	-0.022	-0.021	-0.021
	(0.017)	(0.017)	(0.017)	(0.017)
Household size	0.191***	0.191***	0.191***	0.191***
	(0.008)	(0.008)	(0.008)	(0.008)
Quito	-0.011	-0.016	-0.019	-0.020
	(0.018)	(0.018)	(0.019)	(0.019)
Guayaquil	0.020	0.015	0.016	0.017
	(0.021)	(0.022)	(0.022)	(0.023)
Firm size/1000		0.389	0.194	0.195
		(0.327)	(0.343)	(0.343)
Training			0.026	0.023
			(0.034)	(0.034)
Job tenure/100			-0.017	-0.017
			(0.020)	(0.020)
Job tenure squared/10000			0.002	0.002
			(0.005)	(0.005)
Programmer				0.015
				(0.038)
Computer knowledge				-0.002
				(0.023)
Computer at home				0.011
				(0.025)
Controls for industry	No	Yes	Yes	Yes
Controls for occupation	No	No	Yes	Yes

Note: estimates from linear probability models that also include a constant term. Robust standard errors in parentheses. * indicates significance at the 10%-level; ** indicates significance at the 5%-level; *** indicates significance at the 1%-level. Number of observations equals 2621.

3 Empirical approach

To assess the impact of computer use at work on wages we use various methods. We start with presenting the estimates from OLS-regressions with differing sets of control variables included in the regression. Hence, the first approach is to correct for selection issues by controlling for observables. These results are presented both for the separate cross-sections as well as for the observations that are in the panel data set. We also report results for all observations together, and separately for men and women.

We then exploit the panel nature of our data and estimate models in first differences. Here we present results for all observations but also separately for workers who did not use a computer at baseline and for workers who did use a computer at baseline. Within the group that did not use a computer at baseline, this compares those who started using a computer between baseline and follow-up with the never users. Within the group that uses a computer at baseline, this compares those who stopped using a computer between baseline and follow-up with the always users.

Next we use the variation in intensity of computer use to examine whether the wage premium for computer use works through a causal impact on productivity. The hypothesis is that if using a computer increases productivity it should also be the case that intensity of computer use has a positive impact on wages. We examine this using all the observations in the cross-sections who report to use a computer for at least one hour per week. We also present results from first difference equations in which case identification comes from observations for whom the intensity of computer use changes between 2006 and 2007. As a final test, we examine the pencil premium. Here too, we present results from different specifications and for different (sub)samples, both in levels and in first differences.

4 Results

This section presents the results of our empirical analyses. In subsection 4.1 we present and discuss various estimates of the computer premium. Subsection 4.2 deals with the results related to the intensity of computer use, while subsection 4.3 reports our findings for the pencil premium. Finally, subsection 4.4 reports results from some further robustness checks.

4.1 Computer use

Table 5 shows the coefficients for the computer premium obtained from different specifications, for different years, and for different (sub)samples. Each coefficient comes from a separate regression. The first four columns report results from the separate cross-sections, while the last four columns are obtained from the balanced sample. We base our discussion on the results from the balanced sample, which tend to be a bit larger than the results obtained from the cross-section data sets.

In both years the computer premium is around 40% when we only control for individual background characteristics. Adding controls for firm characteristics (including industry dummies), reduces the premium to around 30%. Again there is almost no difference between the two years. When we also add controls for job characteristics (including occupation dummies), the premium reduces by another 6-7 percentage points. In the final specification we also added variables measuring computer experience and knowledge. In that specification the return is 21.5% in 2006 and 14.1% in 2007, both estimates significant at the 1% level. Estimates tend to be somewhat larger for women than for men. This is especially the case for the most extensive specification in 2007 when the computer premium for women equals 20.1%, while the estimate for men is no longer significant at conventional levels.

The bottom half of the table report fixed effects estimates. In the first three specifications, the level estimates are cut in half and are in the vicinity of 10%. These estimates are still significantly different from zero. The picture changes, however, when we also include the variables that proxy workers' computer experience and knowledge. None of the estimates in the bottom part of the final column is significantly different from zero. This is true for men and women, and also for those who used a computer at baseline, and those who did not. This suggests that the computer premiums that we estimate in the cross-section data and in the less elaborate fixed effects estimations, are in fact returns to computer experience and knowledge.

4.2 Intensity

The productivity interpretation of the computer premium implies that using a computer makes workers more productive. A straightforward implication of this interpretation is that a more frequent use of a computer will then also have a positive impact on wages. To test this implication, Table 6 presents estimates of regressions of (log) wages on the number of hours of computer use per week. Columns (1)-(4) are based on regressions for the separate cross-section data. Columns (5)-(8) are based on regressions for only those observations that are present in both cross-sections. In

Table 5. Estimates of the computer premium

		Unbalanced					Balanced sample				
		(1)	(2)	(3)	(4)	N	(5)	(6)	(7)	(8)	N
OLS 2006	All	0.354***	0.290***	0.218***	0.187***	2621	0.402***	0.313***	0.257***	0.215***	1717
		(0.034)	(0.035)	(0.039)	(0.044)		(0.043)	(0.045)	(0.050	(0.056)	
	Men	0.341***	0.301***	0.219***	0.217***	1593	0.373***	0.304***	0.216***	0.206***	1077
		(0.046)	(0.046)	(0.051)	(0.057)		(0.060)	(0.061)	(0.068)	(0.074)	
	Women	0.370***	0.242***	0.222***	0.133*	1028	0.430***	0.304***	0.343***	0.231***	640
		(0.051)	(0.052)	(0.063)	(0.071)		(0.062)	(0.066)	(0.078)	(0.090)	
OLS 2007	All	0.321***	0.222***	0.156***	0.110***	3298	0.389***	0.273***	0.206***	0.141***	1717
		(0.028)	(0.029)	(0.032)	(0.034)		(0.041)	(0.041)	(0.047)	(0.052)	
	Men	0.268***	0.205***	0.128***	0.076*	2026	0.354***	0.270***	0.192***	0.098	1077
		(0.038)	(0.040)	(0.043)	(0.045)		(0.054)	(0.054)	(0.063)	(0.066)	
	Women	0.384***	0.211***	0.182***	0.1skills46***	1272	0.435***	0.236***	0.217***	0.201***	640
		(0.041)	(0.041)	(0.046)	(0.052)		(0.062)	(0.062)	(0.066)	(0.080)	
Fixed effects	All						0.092**	0.081*	0.083*	0.065	1717
							(0.045)	(0.045)	(0.047)	(0.049)	
	Men						0.092**	0.081*	0.083*	0.065	1077
							(0.045)	(0.045)	(0.047)	(0.049)	
	Women						0.064	0.046	0.037	0.037	640
							(0.062)	(0.064)	(0.067)	(0.070)	
	No computer in 2006						0.135**	0.113*	0.106*	0.058	1374
							(0.067)	(0.065)	(0.064)	(0.068)	
	Computer in 2006						0.095*	0.090*	0.076	0.040	343
							(0.053)	(0.054)	(0.056)	(0.059)	
Controls	Background	yes	yes	yes	yes		yes	yes	yes	yes	
	Firm	no	yes	yes	yes		no	yes	yes	yes	
	Job	no	no	yes	yes		no	no	yes	yes	
	Computer skills	no	no	no	yes		no	no	no	yes	

Note: Each coefficient comes from a separate linear probability model. All observations are weighted with sample weights. Robust standard errors in parentheses. * indicates significance at the 10%-level; ** indicates significance at the 5%-level; *** indicates significance at the 1%-level. Background controls are: years of education, age, age squared, and dummies for female and cities. Firm controls are: dummies for modern sector, informal sector, public sector and payment of social security, firm size and fourteen industry dummies. Job controls are: dummies for training, type of contract (staff, permanent), manager, self employed and salary earner, tenure and tenure squared and nine dummies for first digits of the international standard classification of occupations. Computer skills controls are dummies for being a programmer, knowing how to work with a computer and having a computer at home.

both cases, we restrict the samples to observations who do use a computer. Given the large number of non-users, inclusion of them returns estimates that are very similar to those presented in the previous sub-section, only with a different scaling. Coefficients have been multiplied by 100, so that a point estimate of 0.335 indicates that hourly wages increase by 0.335% for an extra hour of computer use per week.

Most of the estimates are not significantly different from zero. The exception occurs for the cross-section estimates of 2007, where men appear to earn a positive return for using a computer more frequently. The fixed effects estimates are, however, all very small and in some specifications even negative.[4] From this we conclude that among the workers who use a computer, wages do not vary in proportion with the intensity with which they use a computer. This is at odds with the productivity interpretation of the computer premium.

4.3 Pencils

It has been argued by DiNardo and Pischke (1997) that the computer premium just reflects differences in type of jobs, and they show - using data from Germany - that substituting the computer dummy for a pencil dummy gives very similar results. When the computer dummy and pencil dummy are very highly correlated, this "test" does, however, not discredit the productivity interpretation of the computer premium because in that case the pencil dummy will merely pick up the computer effect. In our data the computer dummy and pencil dummy are highly correlated when measured in levels; 0.76 in 2006 and 0.75 in 2007. When measured in first differences, the correlation drops to 0.39, which is still substantial, but not so high that it would mechanically produce the same estimates.

Table 7 reports the results of regressions of the (log) wage on a dummy for using other desk materials (a pencil) at work. The level estimates of men and women together are somewhat smaller than the computer premiums reported in the top panel of Table 5. Looking at the results for men and women separately reveals some differences. While for men the pencil premium and the computer premium are almost equal, the pencil premium for women is much lower than the computer premium for women. The reverse is true for the fixed effects estimates. There we find larger returns to pencil use for women than for men, while the opposite holds for the fixed effects estimates of the computer premium. The results in the most elaborate fixed effects specification indicate, however, that neither men nor women

[4]Results change somewhat when we restrict the samples to workers that use a computer at work for at least 5 or 10 hours per week. In that case the level estimates for 2007 are smaller and no longer significantly different from zero; 0.193 (s.e. 0.234) for at least 5 hours per week, and 0.083 (s.e. 0.259) for at least 10 hours per week.

Table 6. Estimates of the impact of intensity of computer use

		Unbalanced					Balanced sample				
		(1)	(2)	(3)	(4)	N	(5)	(6)	(7)	(8)	N
OLS 2006	All	0.335	0.033	0.092	0.091	523	0.157	-0.174	-0.017	-0.002	343
		(0.193)	(0.198)	(0.206)	(0.206)		(0.231)	(0.224)	(0.237)	(0.238)	
	Men	0.326	-0.057	0.015	0.018	290	0.459	0.010	0.089	0.158	186
		(0.271)	(0.280)	(0.282)	(0.282)		(0.339)	(0.330)	(0.339)	(0.335)	
	Women	0.364	0.157	0.148	0.153	233	-0.343	-0.577	-0.450	-0.452	157
		(0.269)	(0.284)	(0.315)	(0.314)		(0.317)	(0.354)	(0.408)	(0.415)	
OLS 2007	All	0.307**	0.165	0.202	0.180	695	0.446**	0.343*	0.493**	0.425**	358
		(0.134)	(0.132)	(0.128)	(0.127)		(0.197)	(0.198)	(0.202)	(0.205)	
	Men	0.545***	0.370	0.354	0.284	377	0.605**	0.686**	0.745***	0.628**	197
		(0.213)	(0.220)	(0.208)	(0.202)		(0.267)	(0.271)	(0.260)	(0.267)	
	Women	0.041	-0.115	-0.056	-0.062	318	0.310	-0.017	0.140	0.152	161
		(0.158)	(0.162)	(0.165)	(0.168)		(0.302)	(0.323)	(0.347)	(0.348)	
Fixed effects	All						0.038	-0.044	-0.012	-0.011	350
							(0.210)	(0.219)	(0.225)	(0.228)	
	Men						0.236	-0.173	0.001	0.055	191
							(0.329)	(0.391)	(0.360)	(0.352)	
	Women						-0.162	-0.087	-0.133	-0.160	159
							(0.226)	(0.264)	(0.266)	(0.306)	
Controls	Background	yes	yes	yes	yes		yes	yes	yes	yes	
	Firm	no	yes	yes	yes		no	yes	yes	yes	
	Job	no	no	yes	yes		no	no	yes	yes	
	Computer skills	no	no	no	yes		no	no	no	yes	

Note: Each coefficient comes from a separate regression. All coefficients have been multiplied by 100. All observations are weighted with samples weights. Robust standard errors in parentheses. * indicates significance at the 10%-level; ** indicates significance at the 5%-level; *** indicates significance at the 1%-level. Background controls are: years of education, age, age squared, and dummies for female and cities. Firm controls are: dummies for modern sector, informal sector, public sector and payment of social security, firm size and fourteen industry dummies. Job controls are: dummies for training, type of contract (staff, permanent), manager, self employed and salary earner, tenure and tenure squared and nine dummies for first digits of the international standard classification of occupations. Computer skills controls are dummies for being a programmer, knowing how to work with a computer and having a computer at home.

earn a significant pencil premium. This is also true for the sub-samples of pencil winners and pencil losers.

Although the estimates for the pencil premium in the various specifications and for different sub-samples, does not completely mimic the results for the computer premium, they are by and large consistent with them. Replacing the computer dummy by a pencil dummy in the cross-section regressions would also have led to the conclusion that there is a substantial premium in both years, and for both genders. The results in the bottom panel indicate, however, that these estimates are to a large extent reflecting unobserved fixed effects.

4.4 Further robustness checks

To probe the robustness of the results, we now discuss the findings for some alternative sub-samples and specifications. First, we estimate the computer premium for the subsample of workers who hold the same job during the two survey moments. For this group we can exclude that the fixed effects estimates of the computer premium capture the impact of another job.[5] Of the 1717 observations in the balanced panel, 82 percent kept the same job. Exclusion from the sample of 18 percent job changers hardly affects the estimates. For the specification with all control variables, the fixed effects estimate of the computer premium equals 0.061 (s.e. 0.053). For the return to intensity of computer use this is 0.050 (s.e. 0.167) and for the pencil premium 0.026 (s.e. 0.049). These estimates are all very similar to those reported in the bottom parts of the final columns of Tables 5 to 7. The same holds for the estimates using the other specifications.

Next, we restrict the sample to workers who report that they know how to use a computer. Of the 2006 cross-section sample, 38 percent claims to know how to use a computer. For the 2007 cross-section sample this percentage equals 41. In the balanced panel these percentages are 38 and 37, respectively.[6] As Table 3 shows, there are no people reporting that they use a computer without knowing how to use it, while around a quarter of those who do not use a computer say that they know how to use it. Based on the most elaborate specification, we find estimates of the computer premium equal to 0.189 (s.e. 0.045) for the subsample of the 2006 cross-section, 0.109 (s.e. 0.036) for the subsample of the 2007 cross-section, and 0.059 (s.e. 0.055) for the fixed effects estimate. These estimates are only slightly lower than the estimates reported in Table 5.

[5]This implies that we restrict the sample to workers who in the follow-up report a job tenure exceeding 14 months. The data set does not contain firm identifiers. Otherwise we could have included firm fixed effects in addition to the worker fixed effects.

[6]109 members of the balanced panel lost their computer knowledge, while 95 gained it.

Table 7. Estimates of the pencil premium

		Unbalanced					Balanced sample				
		(1)	(2)	(3)	(4)	N	(5)	(6)	(7)	(8)	N
OLS	All	0.321***	0.237***	0.147***	0.110***	2621	0.348***	0.235***	0.144***	0.097*	1717
2006		(0.035)	(0.037)	(0.040)	(0.043)		(0.045)	(0.046)	(0.051)	(0.053)	
	Men	0.334***	0.269***	0.163***	0.145***	1593	0.373***	0.273***	0.150**	0.131*	1077
		(0.048)	(0.049)	(0.054)	(0.057)		(0.064)	(0.064)	(0.067)	(0.070)	
	Women	0.296***	0.161***	0.135**	0.059	1028	0.303***	0.174**	0.176**	0.071	640
		(0.050)	(0.056)	(0.064)	(0.067)		(0.063)	(0.072)	(0.081)	(0.083)	
OLS	All	0.296***	0.184***	0.111***	0.072**	3298	0.367***	0.235***	0.165***	0.114**	1717
2007		(0.030)	(0.030)	(0.034)	(0.035)		(0.043)	(0.043)	(0.048)	(0.049)	
	Men	0.269***	0.210***	0.119***	0.083*	2026	0.368***	0.285***	0.194***	0.138**	1077
		(0.042)	(0.042)	(0.047)	(0.048)		(0.057)	(0.054)	(0.062)	(0.063)	
	Women	0.312***	0.116**	0.096*	0.055	1272	0.350***	0.126*	0.113	0.079	640
		(0.042)	(0.045)	(0.051)	(0.053)		(0.067)	(0.073)	(0.078)	(0.081)	
Fixed	All						0.063	0.056	0.045	0.036	1717
effects							(0.042)	(0.041)	(0.042)	(0.043)	
	Men						0.044	0.022	-0.005	-0.007	1077
							0.060	0.061	0.062	0.064	
	Women						0.080	0.091*	0.093*	0.057	640
							(0.057)	(0.054)	(0.053)	(0.055)	
	No pencil in 2006						0.018	0.003	-0.024	-0.037	1438
							(0.059)	(0.060)	(0.059)	(0.060)	
	Pencil in 2006						0.109*	0.129**	0.089	0.083	279
							(0.056)	(0.052)	(0.056)	(0.061)	
Controls	Background	yes	yes	yes	yes		yes	yes	yes	yes	
	Firm	no	yes	yes	yes		no	yes	yes	yes	
	Job	no	no	yes	yes		no	no	yes	yes	
	Computer skills	no	no	no	yes		no	no	no	yes	

Note: Each coefficient comes from a separate regression. All observations are weighted with sample weights. Robust standard errors in parentheses. * indicates significance at the 10%-level; ** indicates significance at the 5%-level; *** indicates significance at the 1%-level. Background controls are: years of education, age, age squared, and dummies for female and cities. Firm controls are: dummies for modern sector, informal sector, public sector and payment of social security, firm size and fourteen industry dummies. Job controls are: dummies for training, type of contract (staff, permanent), manager, self employed and salary earner, tenure and tenure squared and nine dummies for first digits of the international standard classification of occupations. Computer skills controls are dummies for being a programmer, knowing how to work with a computer and having a computer at home.

Finally, we examined the robustness of the estimates of the computer premium if the pencil dummy is included as an additional regressor. For the most extensive specification, the estimates from this specification are 0.178 (s.e. 0.052) for the 2006 cross-section, 0.095 (s.e. 0.043) for the 2007 cross-section, and 0.059 (s.e. 0.056) for the fixed effects estimate. Again, these results are very similar to the main results.

5 Conclusions

The large increase in wages inequality during the past decades has triggered a debate about its causes. Skill bias technological change has been proposed as one of the important factors. Related to this, various studies have analyzed the effect of the use of computers at work on wages. Whether a computer premium really reflects the impact of technology on productivity depends on the role of unobservables. DiNardo and Pischke (1997) found also large differences for on the job the use of calculators, telephones, pens or pencils, or for those who are sitting while working.

The empirical evidence on the computer premium in developing countries is thin. Our study is among the first presenting estimates of the computer premium for a developing country while addressing endogeneity issues. Using cross-section data, we find a computer premium in the vicinity of 20%, for a specification that includes a rich set of control variables. This is in line with previous findings for the developed part of the world.

Exploiting the fact that we have repeated observations from the same individuals, we estimate various fixed effects models. For most specifications, this cuts the estimate of the computer premium in half. In a fixed effects specification that also includes proxies for workers' computer experience and knowledge, the computer premium ceases to be significantly different from zero. This suggests that the computer premium is for a large part reflecting the return to computer experience and skills. The results for the pencil premium and the intensity of computer use are consistent with this interpretation. This implies that also in a country in which the penetration of computers and computer knowledge are more limited, the computer premium is more likely to reflect unobserved differences between workers and/or jobs than a real productivity effect.

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