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# Computer Adoption and Returns in Transition

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Abstract

Across nine transition economies, it is the young, educated, English-speaking workers with the best access to local telecommunications infrastructures that work with computers. These workers earn about 25% more than do workers of comparable observable skills who do not use computers. Controlling for likely simultaneity between computer use at work and labor market earnings makes the apparent returns to computer use disappear. These results are corroborated using Russian longitudinal data on earnings and computer use on the job. High costs of computer use in transition economies suppress wages that firms can pay their workers who use computers.

JEL Classification: O, P2, J31
Key Words: Computer Adoption, Earnings, Returns, Sorting, Technology, Eastern Europe, Central Asia

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Computer Adoption and Returns in Transition

## I. Introduction

Starting in the 1980s, there was a general trend toward rising income inequality in European and North American economies. A large literature has attributed at least a share of the rising inequality to rising returns to education associated with skill-biased technical change, particularly in information technologies (IT).[1] Because more educated workers are presumed to have skills that are complementary with capital, these technological changes are responsible for a systematic shift in labor demand toward educated labor that has raised earnings for IT users in many OECD countries.[2] Corroborating evidence can be found in the connection between IT investments and economy-wide growth in labor productivity in the OECD economies.[3] By raising the productivity and/or lowering the cost of capital, firms can afford to raise pay for educated labor.

Transition economies have been characterized by rapidly increasing returns to education (Brainerd, 2000; Fleisher et al, 2005; Orazem and Vodopivec, 1995). A common rationale for this result is that under the previous planned system, centrally dictated wages artificially limited income inequality by raising pay for the least skilled through transfers from the most productive sectors and workers in the economy. When the centrally dictated wage system was disabled, market forces raised relative pay for educated workers to levels more similar to those observed in the west.

Past research has not established whether rising returns to schooling in transition economies can also be linked to information technologies as in the OECD economies. There is only weak corroborating information that IT has accelerated growth in transition economies.[4] One weakness of past research on adoption of and returns to information technologies in transition economies has been the lack of detailed data on computer use and earnings. Most studies rely on data aggregated to the country level, and so household data needed to estimate adoption of or returns to computer adoption have not been available.

There are several reasons why IT technologies may not lead to the same productivity or wage gains in transition economies as in the OECD economies. One is that the telecommunications infrastructure in the formerly planned states is underdeveloped. While the Soviet economy invested heavily in capital, those investments were weighted toward the military and manufacturing sectors that generated virtually no return (Easterly and Fischer, 1995). Consequently, most of the formerly planned economies entered transition with poorly developed communications systems compared to the west. For instance, even after ten years of transition, teledensity, the number of phone lines per 100 residents averaged 19 in former Soviet states compared to 41 in Europe and 66 in the United States. (ITU, 2003).

A second factor is that IT is extremely expensive in transition countries relative to local ability to pay. State-run telecommunications monopolies have not had to face foreign or domestic competition, allowing them to keep prices high and service quality low compared to the west. Often, only corporate clients, banks, and foreign representative offices can afford these services. One month of Internet service costs on an average 13.5% of per capita monthly income in these nine countries, the lowest cost being in Bulgaria at 1.4% of monthly income. In contrast, a month of off-peak service costs only 0.2% of monthly income in the U.S., 0.7% in the U.K. and 0.9% in France.[5] Revin's (2001) analysis for Uzbekistan found that one hour of daytime dial-up connection provided by the official telecommunications monopoly UzPAK cost 8% of the average monthly salary. One hour of nighttime dial-up service costs about half that, but is still clearly unaffordable for the average citizen. As we argue theoretically, high computer costs can suppress wage differentials between workers using and not using computers on the job, suggesting that transition economies may not have a digital divide in earnings.

Cross-country studies of computer and Internet usage rates have pointed to high prices, lack of telecommunications infrastructure and regulatory constraints on competition along with low per capita incomes and/or education levels as reasons why IT use lags in transition economies.[6] And they do lag: as of 2002, the ratio of personal computers per 100 residents ranged from a low of 0.9 in Armenia to 8.9 in Russia, well below the 20 PCs per 100 resident in Europe or 62.5 PCs per 100 residents in the U.S.. Shrinking this digital divide across countries will require improving the IT infrastructure as well as improving the human capital in transition countries.

This study addresses two questions not addressed by the cross-country studies of IT use: 1) what is the nature of the digital divide within as well as across transition economies? and 2) what can we tell of the impact of the digital divide on earnings inequality in transition countries? These questions are addressed using household data from nine formerly planned economies: Armenia, Belarus, Bulgaria, Georgia, Moldova, Romania, Russia, Ukraine, and Uzbekistan.

We find that, as in OECD countries, it is the young, educated, urban workers in transition economies that are the most likely to use computers at work. Computer usage is also closely tied to the quality of the telecommunications infrastructure that would improve the productivity of computers. However, computer usage at work is particularly tied to the ability to speak foreign languages, especially English. Finally, at least part of the variation in computer usage is driven by individual interests: particularly among individuals with interests in science or politics.

Has the digital divide served as a source of income inequality in transition economies? Our findings suggest the answer is no. When computer use is treated as exogenous, estimated returns are comparable to the 20% found in studies in Europe and North America. However, controlling for likely simultaneity in computer adoption causes the estimated returns to become negative and insignificant compared to the modest positive returns found for OECD countries. These results are consistent with a model in which the high costs of operating computers in transition countries suppresses wage differentials between firms with and wiothout computers. Our findings suggest that thus far, the digital divide has not exacerbated income inequality in transition economies.

The rest of the paper is organized as follows. Section II provides a brief literature review along with a simple model of computer adoption and income returns to computer adoption. Section III describes data and variables used in the study, while Section IV describes our estimation strategy. The results relating to the determinants of computer adoption are presented in Section V. Section VI then presents results that relate computer adoption to earnings. Section VII concludes.

## II. Theory and Literature Review

A. Computer adoption

We assume that an individual chooses a job involving computer use if the expected utility dominates that of other jobs not involving a computer. The expected utility from computer adoption is approximated by

(1) $$V_1(C_{ij} = 1; Y_{ij}, H_{ij}, Z_{ij}, T_{ij}, \xi_{ij}, \tau^c_{ij}),$$

where $C_{ij}$ is a dummy variable indicating computer use on a job available to individual i in country j, $Y_{ij}$ is the income earned at that job, $H_{ij}$ is a vector of individual skills, $Z_{ij}$ is a vector of demographic variables, $T_{ij}$ is a vector of locally available technologies such as telecommunications infrastructure that alter the cost or productivity of using a computer, $\xi_{ij}$ is unobservable individual ability which is specific to job j, and $\tau_{ij}^{c}$ is the hedonic return to computer use on the job. Similarly, the utility from a job not involving computer use is given by

(2) $$V_0(C_{ij} = 0; Y_{ij}, H_{ij}, Z_{ij}, T_{ij}, \xi_{ij}) .$$

The probability of selecting a job involving computer use can be written as

$$P(C_{ij} = 1) = P\left\{V_1(C_{ij} = 1; Y_{ij}, H_{ij}, Z_{ij}, T_{ij}, \xi_{ij}, \tau_{ij}^{c}) - V_2(C_{ij} = 0; Y_{ij}, H_{ij}, Z_{ij}, T_{ij}, \xi_{ij}) > 0\right\}.$$

The linear approximation will have the form

(3) $$P(C_{ij} = 1) = P\left\{\alpha_0 + \alpha_1 Y_{ij} + \alpha_2 H_{ij} + \alpha_3 Z_{ij} + \alpha_4 T_{ij} + \alpha_5 \tau_{ij}^{c} + \alpha_6 \xi_{ij} > 0\right\},$$

where the parameters, $\alpha_k$**,** indicate the relative utility of applying the $k^{th}$ attribute on a job using computers relative to a job not using computers. If $\alpha_k > 0,$ then the $k^{th}$ factor can be interpreted as being complementary with computer use on the job. $\alpha_6 \xi_{ij}$ is an error term reflecting the difference in the productivity of unobserved ability in jobs with and without computers. The error term is assumed to be normally distributed with mean zero and constant variance.

Past studies of computer adoption in western economies have generated consistent predictions and empirical regularities of how human capital measures, $H_{ij}$, should affect incentives to adopt computers. Education is presumed to rise with computer use, both because it increases the ability to learn how to use the computer and because of presumed complementarity in production between education and information technologies. These presumptions are consistent with the empirical findings of Bartel and Lichtenberg (1987), Doms, Dunne and Troske (1997), Autor, Katz and Krueger (1998), and Abdulai and Huffman (2003) among others.

As an individual ages, the length of time to recoup the investment in computers decreases. Therefore, the young have the greatest incentive to adopt computers. This presumption is also consistent with empirical studies based in western economies including studies by Huffman and Mercier (1991).

Computer adoption is expected to vary with income for several reasons. Computers provide consumer services such as word processing, record keeping, communication and information that households value. The demand for these consumption services are expected to increase with income. Second, in transition economies, liquidity constraints are prevalent and so the cost of borrowing is likely to fall as household wealth or available collateral increases. Therefore, computer adoption is likely to increase with household income or wealth. Even in western economies where liquidity constraints are less severe, there is a strong positive relationship between computer use and household income (Schirmer and Goetz, 1997; Fairlie ,2004). For transition economies, therefore, the relationship is expected to be even stronger. [7]

There is no strong prediction about the expected impact of household demographic variables on computer adoption, but past studies have shown that computer use is less common among minority households and rural households. Several studies in the United States identified a significant race effect in computer adoption (Hoffman and Novak ,1998; NSF ,2001; Fairlie, 2004).

Computer adoption is more expensive when available telecommunications infrastructure, $T_{ij}$, is of poor quality. While $T_{ij}$ will vary across countries, it may vary within countries as well, particularly between more and less densely populated areas of the country. Cross-country studies such as those by Muller and Salsas (2003) and Chinn and Fairlie (2004) have found that the level of computer or Internet use in a country can be tied to the proportion of households with telephone lines, a measure of telephone infrastructure. We control for cross-country differences in telecommunication infrastructure with a series of country dummy variables. Within country, we created a measure of local access to satellite or cable television access. These services can enhance the productivity of computer usage on the job by lowering the cost and/or increasing the productivity of Internet applications.

There is an additional reason for the use of computers in transition economies that is taken somewhat for granted in the OECD economies: that computers expand greatly the information base available to remotely located individuals. Individuals with strong interest in accessing current local or global political, scientific, or cultural information will have an incentive to adopt computers, even if the information has no direct economic return. This source of taste for computer access, $\tau_{ij}^{c}$, is particularly important in transition economies where foreign information sources are frequently viewed as more reliable than domestic, state-owned media. The young are the most interested in learning about news abroad and in communicating with foreign peers and the young are most likely to list information obtained on the Internet as reliable, whether or not they have ever used the Internet (InterMedia, 2001).

Eighty percent of web sites in the world are in English. Most of the rest are in a language of international commerce (French, German, Italian, Japanese or Spanish). Consequently, language skills would be expected to be closely tied to computer adoption, a hypothesis consistent with Fairlie's (2004) findings for the U.S.. Language skills are likely to be even more important in the computer adoption decision in transition economies where web sites in the native language are a small fraction of the web sites available in English or the others listed above.

B. Returns to computer adoption.

The standard approach to estimating returns to human capital investments, following Mincer (1974) is to estimate an equation relating the logarithm of earnings to measures of education and work experience. Following Krueger (1993), the enhanced log earnings function can be written as

(4) $\ln Y_{ij} = \beta_0 + \beta_1 C_{ij} + \beta_2 H_{ij} + \beta_3 Z_{ij} + \varepsilon_{ij}$,

where the coefficient, $\beta_1$, is interpretable as the rate of return from use of a computer. The variables are defined as before and $\varepsilon_{ij} = \alpha_6 \xi_{ij} + \phi_{ij}$ is an error term that reflects the worker's unobserved ability plus a pure random error. If $\xi_{ij}$ is uncorrelated with the regressors, then ordinary least squares estimation of (4) will yield unbiased estimates of $\beta_1$. However, if computer adoption depends on unobserved abilities as in (3), this is almost certainly not the case unless the worker's unobserved abilities are equally productive in both jobs (i.e. $\alpha_6 \xi_{ij} = 0$). The likely correlation between $C_{ij}$ and $\xi_{ij}$ will cause bias in the least squares estimation of $\beta_1$ in (4), although the direction of bias is difficult to predict. If higher ability raises the probability of computer adoption and there are no other sources of bias in (4), we would expect positive values of $\xi_{ij}$ to be positively correlated with $C_{ij}$, and so least squares estimates of $\beta_1$ would be biased upward.

This formulation can be shown to be consistent with a model in which perfectly competitive firms decide whether or not to invest in computer technologies at a cost that is highest in markets with poor IT infrastructure. [8] Workers decide whether to work at firms with or without computers based on the relative utility of the two jobs, as in (3). Wages paid in the firms with computer technologies will be equal to the marginal product of labor net of the computer cost while wages at other firms are equal to the lower marginal product. The equilibrium shows that workers in the firms with computers have both more observed and unobserved human capital than do workers in firms without computers. This sorting depends on the productivity and cost of computer adoption and on the worker tastes for computers.

The role of computer costs is particularly important: as the IT infrastructure gets weaker, fewer firms invest in computer technologies, wages for all workers decline, and the gap in pay between workers working with and without computers gets smaller. However, holding wages fixed, workers with stronger tastes for computer use will sort more readily into firms with computers. It is even possible that if the IT infrastructure is very weak and the worker tastes for working with computers are sufficiently strong, wages in firms using computers may end up below the wage the same worker would earn in a firm without computers.

This model also suggests how we could identify $C_{ij}$ in (4). We require variables that vary the probability of computer use without directly raising income. From (3), the best candidates available would be expected to be measures of $T_{ij}$ and $\tau_{ij}^{c}$, but the equilibrium model found that all wages rise with $T_{ij}$. Consistent with this prediction, local access to satellite or cable television, our measure of within-country variation in technology infrastructure, failed tests of exogeneity with respect to earnings. However, our measure of taste for information $\tau_{ij}^{c}$, the individual's self-assessment of the importance of having current information on politics or scientific and technological advances, did pass overidentification tests (Wooldridge, 2002, p. 201).

In all specifications attempted, when computer use at work is treated as exogenous, we find positive and significant returns to computer use. However, when the endogeneity of the choice to work at a job with computers is controlled, the returns are insignificant, suggesting that the least squares estimates overstate the true returns to computer use in transition economies.

We cannot estimate (3) directly because of the presumed reverse causality between income and computer utilization. Instead, we can insert (4) into (3) and solve for $C_{ij}$. The resulting reduced form of the computer adoption decision will be

(3') $$P(C_{ij}=1)=P\left\{\alpha_0^{'}+\alpha_2^{'}H_{ij}+\alpha_3^{'}Z_{ij}+\alpha_4^{'}T_{ij}+\alpha_5^{'}\tau_{ij}^{c}+\xi_{ij}^{'}>0\right\}$$

Equation (3') must be estimated using nonlinear estimation to accommodate the limited dependent variable. Our strategy is to estimate (3') to generate a predicted value of $C_{ij}$, $\hat{C}_{ij}$, which is then used in place of $C_{ij}$ in the second-stage equation (4). Because $\hat{C}_{ij}$ will be purged of the impact of $Y_{ij}$ on $C_{ij}$, $\hat{C}_{ij}$ will be uncorrelated with $\xi_{ij}$. This two-step process is not efficient and so the standard errors will be biased. Therefore, we use a bootstrapping procedure to generate corrected standard errors for our estimates of equation (4). [9]

Because these taste measures are an admittedly thin source of identification, we replicate our results below using longitudinal data to remove the unobserved ability component $\xi_{ij}$ on the assumption that it is a time-invariant fixed effect. Results are very consistent with our instrumental variables results.

**III. Data**

This study utilizes data collected by the InterMedia Survey Institute based in Washington D.C. The data was collected using a stratified random sample of the population in nine transitional economies in Eastern Europe and Central Asia in the year 2000. The method involved randomly selected household addresses from a set of randomly selected postal districts. The survey was administered through face-to-face interviews conducted through local agencies. Countries included Armenia, Belarus, Bulgaria, Georgia, Moldova, Romania, Russia, Ukraine, and Uzbekistan. Because of the need to tie computer use to earnings, we restricted our data set to working individuals between the ages of 18 to 65. The pooled sample included 5382 observations. Useable sample sizes varied from 275 in Georgia to 907 in Belarus.

The survey included a wealth of information on access to and attitudes towards information, media, democracy and politics, the primary purpose for the survey. However, it also included questions on computer usage, availability of local telecommunications services, and household income as well as information on human capital and other demographic information, which made the data adaptable for a study of computer adoption and returns to usage in transition economies.

Summary statistics for all the variables utilized in the study are presented in Table 1. Country-level averages are reported in Table 2. The first dependent variable used in the analysis is a binary variable on computer use at work. The computer use measure is inferred from responses to questions asking whether an individual has used a computer, and for those answering affirmatively, responses to a question asking whether they use a computer at work. Individuals who use a computer but not at work and individuals who never use a computer are in the reference group. At 14%, computer use is comparatively low relative to OECD countries. In our working sample, 13% access computers at work but only 4% access computers at home. That illustrates the potential importance of computer access at work as a job perquisite.

The measure of earnings is the log of household monthly income in dollars. The survey reports income in ranges of the home currency instead of exact values, so we use the midpoint of the range for income.[10] Monthly income is converted to U.S. dollars using 2000 Purchasing Power Parity exchange rates. Average monthly household income varied from a low of $29 in Moldova to a high of $164 in Bulgaria. To avoid measurement errors in the currency exchange, the regressions use country-level dummy variables that will correct for variation in currency values across countries.

Use of household income is not ideal because of the possibility of multiple earners in the household. Household size varies from under 3 in Russia to nearly 6 in Uzbekistan. We control the problem in two ways. First, in the full sample, the regression controls for the number of potential earners in the household using information on household composition (number of household members and information on marital status). Second, we replicate all results using only the subsample of male workers and again using the subsamples of two person and one person households so that household income can be equated with individual income. Finally, we make use of an alternative longitudinal data set, the Russia Longitudinal Monitoring Survey (RLMS) that has information on individual earnings. Qualitative results are similar across the various samples which should help to allay concerns that our results are driven by measurement problems.

The explanatory variables are subdivided into four categories: human capital, demographic, taste, and telecommunications infrastructure. Human capital measures, $H_{ij}$, show that all these countries are reasonably highly educated with averages at 12-14 years. Ability to speak English is somewhat rare at 11% with 10% speaking another G-7 language. Language skills vary extensively: the proportion speaking English ranges from 3% in Uzbekistan to 28% in Romania. Ability to speak other G-7 languages correlates highly with ability to speak English.

There is also variation across and within countries in telecommunications access. Past cross-country studies have used country averages of telephone, cable or satellite access as measures of telecommunications infrastructure, but our use of country dummy variables controls for this source of cross-country variation. Our remaining measure of $T_{ij}$ is the availability of cable or satellite service in the local community. Note that this measure is not merely a proxy for more populous areas, as we also include the dummy variable that indicates whether the individual resides in an urban area. Bulgaria and Romania have the best local telecommunications infrastructure access, while these complementary technologies are nearly absent in Armenia.

The key measure of taste for information $\tau_{ij}^{c}$ is based on individual assessments of personal interest in various topics. Responses vary from “Not at all interested,” “Not very interested,” “Somewhat interested,” or “Very interested.” Because computer technology aids information gathering and processing, individuals who place greater priority on having current information should be more motivated toward computer adoption.

The most important of the demographic variables is the urban dummy variable that is included to help control for underlying differences in prices between metropolitan and rural markets within a country. Roughly two-thirds of the sample are urban residents, ranging from 39% in Uzbekistan to 81% in Bulgaria.

## IV. Determinants of computer use at work

The computer adoption equation (3’) is our means of identifying the nature of the digital divide within these transition economies. Few household-level studies exist of technology adoption in transition economies more generally, much less of IT adoption. These estimates will help establish who in the emerging market economies will be most likely to invest in the skills needed for new technologies generally, and who will adopt the IT technologies needed to integrate into the global economy.

Results of the probit estimation for the pooled sample for nine countries are included in Table 3. Dummy variables for each country were included but not reported. The marginal effects are reported to ease interpretation. The variables can explain 24% of the variation in computer use on the job.

Human capital measures have a large effect on the probability of computer use at work. Age has a negative and significant effect on computer use, although the magnitude of the effect is small—a two percentage point decrease for every 10 years of age[11]. Formal schooling has a substantial effect on computer adoption. Every year of education increases the probability of computer use by 2 percentage points, roughly the same amount as a ten year decrease in age. Relative to an individual with average education (12.6 years), a college graduate is 52% more likely to use a computer at work. This skill technology complementarity is similar to that found in the U.S. and in other OECD countries (Katz and Autor, 1999; Autor et al.,1998).

More unique is the very large effect of language ability on the likelihood of accessing a computer at work. Those who speak English are 11 % more likely to use a computer at work than those who don't. Those who speak other G7 languages are 3 % more likely to use a computer at work. Speaking Russian has a positive but smaller and statistically insignificant impact on computer use.

Urban dwellers are 5% more likely to use computers on the job. Access to cable or satellite service has an effect 3 times larger, the largest marginal effect of any factor in the model. Even with small average computer usage rates, it is clear that there is a substantial urban-rural digital divide in transition economies. Some of this may reflect underlying tastes of residents if those wishing to use IT technologies move across communities to areas with better infrastructure. Nevertheless, our results still find a substantial role for individual variation in human capital, as equalizing access to telecommunications infrastructure will not eliminate the digital divide.

Household size and marital status did not influence the likelihood of computer use at work. Males and females were equally likely to use computers. Except for urban residence, computer use was driven by human capital and telecommunications infrastructure, a result very consistent with the cross-country evidence presented by Chinn and Fairlie (2004).

Taste for information also has an effect on computer usage at work. Those very interested in political information are 4% more likely to use a computer at work than are those with no interest whatsoever. Nearly identical effects exist for science and technology information, albeit somewhat less precisely estimated. The null hypothesis that the coefficients on the two taste for information measures were jointly zero in the computer adoption equation was easily rejected, and so these instruments will have some power to distinguish computer users from nonusers.

To check the stability of these results over the various subsamples described in the data section, we replicated the estimation using the sample of employed males only; the sample of employed individuals in households with only one or two members; and the sample of workers who are the sole member of their household. The last sample only had 222 observations and lacked precise estimates, but the qualitative results were similar to the other three samples.

Our greatest concern was that a model of individual choice could differ in the context of a household with multiple decision-makers. A comparison of the estimated marginal effects across samples in Table 3 shows that the concern was unfounded: the results are very consistent across samples. In all samples, the instruments passed the test of joint significance, albeit only at the tenth percentile for the male worker subsample.

We also replicated the estimation for individual countries for which we had sufficient observations. Partial results for the key variables are reported at the top of Table 5. Again, the results are qualitatively similar, although significance suffers with the smaller samples. Signs are identical for all human capital measures and for urban residence. The taste measures are at least marginally jointly significant in four of the six countries and signs disagree only for interest in science and technology.

We can use the variation in computer adoption models across countries to explore the role of the various factors in the cross-country digital divide. Findings of the observed difference between computer adoption in each country and the mean adoption rate across all countries are reported in the middle section of Table 5. Some apparent regularities arise, although they are not completely consistent across countries. Good infrastructure explains higher adoption rates in Bulgaria and Romania and weak infrastructure retards adoption in Uzbekistan. Strong human capital endowments help the adoption rates in Romania and Ukraine and weak human capital limits adoption in Uzbekistan. The urban share of the population increases adoption rates in Belarus, Bulgaria and Russia and lowers adoption rates in Uzbekistan.

Overall, the factors responsible for the digital divide in transition countries are quite similar to those identified in western economies. The average user of computer technologies could be of any sex, but he/she is likely to be younger, urban, better educated, well informed, speaking a major trade language, and living in an area with infrastructure that can support computer technology. These conclusions are consistent across various subsamples. They suggest that there is great potential for digital divides within and between transition countries including divides between education groups, between urban and rural areas, between areas with and without telecommunications infrastructure, between generations, and between those who do and do not speak the languages of international commerce. In the next section, we assess whether these divides will exacerbate income inequality in these countries.

## V. Returns to computer adoption

In the second stage of our analysis, we use a Mincerian log earnings function supplemented by actual and predicted use of computers to measure the extent to which the digital divide has led to earnings inequality. The sample sizes vary modestly because some individuals did not report income. Results are reported in Table 4. Across all specifications, the earnings functions fit quite well with over 50% of the variance explained by the model. [12]

When computer use is treated as exogenous, the estimated returns are positive, significant, and at roughly 25% return, toward the upper end of the range of returns reported from least squares analysis using similar specifications in western economies.[13] Noting that our taste-based instruments may be suspect,[14] when instruments are used to correct for the endogeneity of computer usage at work, the estimated returns become insignificant.[15] Two important inferences follow. First, the finding of upward bias in least squares estimates of the returns to computer adoption are consistent with a model in which the workers that take jobs involving computers are those with unobserved atypical abilities. The higher wages earned by these workers are attributable to this unobserved ability and not to the computer usage *per se*. Second, computer usage at work is not exacerbating the rise in income inequality in these transition economies, at least thus far.

The first result merits some elaboration. It is common for endogeneity corrected results in OECD countries to be smaller than the least squares estimates, but they are still usually positive in the 2-10% range.[16] As mentioned above, competitive firms who adopt computers will set pay net of the cost of computer use. These transition economies have relatively weak IT infrastructure and high Internet costs compared to the OECD economies that were the focus of earlier studies. The higher are the costs of computer use, the lower will be the wage differential between firms with and without computers. Our corrected estimates are lower, albeit not precisely estimated, than the comparable findings using OECD country data, suggesting that the wages of workers using computers in transition economies may be artificially low because of the high costs firms face in acquiring and using computer technologies.[17] The same story is found at the bottom of Table 5 where we report estimates for the subset of countries where we have sufficient observations.

The other variables have interest as well. All of the human capital measures increase in magnitude in the IV estimation. Returns to language are substantial: 18% for knowing English and 12% for knowing another G7 language. There is no significant return to speaking Russian. Undoubtedly, part of the large return to these languages is due to the relatively small proportion who hold these language skills, and so we would expect the marginal returns to be bid downward as more individuals acquire these languages. Urban dwellers and men earn more than rural residents and women respectively. The magnitudes of these gaps are somewhat smaller than their counterparts in OECD countries.

There is a substantial return to local telecommunications infrastructure, consistent with Piatkowski's (2004) conclusion regarding the role of IT investment on growth. It is interesting that wages generally rise with local IT infrastructure access, but not atypically for individuals using the local IT technologies at work. Apparently, due to network effects, the returns to IT access are shared more broadly in the population than just to the subset using the technology directly.

We were concerned that household income might reflect the earnings of others in the household and not just the respondent. While we correct at least partially for the number of potential earners in the household by controlling for marital status and the number of household members, we also examined how robust our results were to alternative subsamples that limited the number of multiple earners. Presumably, working women would be more likely to have a working spouse, and so the restriction to male workers should have reduced the possible bias from multiple earners. The results are hardly changed at all. When we restrict the sample to households with only one or two members, again the estimated returns hardly change. When we further restricted the sample to include only single member households, the qualitative results remained the same, but the coefficient estimates lost precision due to the very small samples. In every subsample, returns to computer use were positive and significant when treated as exogenous but insignificant when treated as endogenous.

## VI. Longitudinal Analysis

The cross-country cross-sectional analysis leaves open the possibility that the conclusions regarding the returns to computer use in transition economies are influenced by individual-specific fixed effects such as unmeasured ability or ambition that may be correlated with the regressors in the earnings function (4). Despite passing the overidentification tests, our instruments underlying the instrumental variable estimation in Tables 4 and 5 might be questionable. Several papers (Entorf et al, 1999; Dolton and Makepiece, 2004; Krashinsky, 2004) have used longitudinal data on individuals to control for unobserved ability in estimating the returns to computer use. These difference-in-differences estimates rely on changes in computer use to identify the effect of computer use on the growth in earnings. We follow that strategy to assess the extent to which our results may be biased by missing controls from unobserved individual heterogeneity.

The Russia Longitudinal Monitoring Survey (RLMS) provides longitudinal data on earnings and includes a question on whether the respondent used a computer on the job. The same questions are repeated annually from 2000 to 2004, allowing us an alternative way to assess whether computer use on the job earns atypical returns in transition economies. Suppose that two successive years of earnings data can be described by the following equations

(5A) $\ln Y_{i1} = \beta_{01} + \beta_1 C_{i1} + \beta_{21} H_i + \beta_{31} Z_i + \xi_i + \phi_{i1}$

(5B) $\ln Y_{i2} = \beta_{02} + \beta_1 C_{i2} + \beta_{22} H_i + \beta_{32} Z_i + \xi_i + \phi_{i2}$

where $\xi_i$ is an unobserved, time invariant ability, $H_i$ and $Z_i$ are, respectively, time invariant measures of human capital and demographic characteristics, and $\phi_{it}$ is a random error. Computer use on the job, $C_{it}$, varies over time. We allow the returns to human capital and demographic attributes to vary over time, as has been commonly found in the early transition (Brainerd (2000), Fleisher et al (2005)).

In the specification above, the likely covariance between $\varphi_i$ and $C_{it}$ will lead to biased estimates of the returns to computer use in ordinary least squares estimation of a single cross-section as in (5A). Differencing the data eliminates $\varphi_i$ as in

(6) $\ln(\frac{Y_{i2}}{Y_{i1}}) = (\beta_{02} - \beta_{01}) + \beta_1 (C_{i2} - C_{i1}) + (\beta_{22} - \beta_{21}) H_i + (\beta_{32} - \beta_{31}) Z_i + (\phi_{i2} - \phi_{i1})$

Assuming the differenced random error terms are uncorrelated with the change in computer use on the job, least squares estimation of (6) will yield an unbiased measure of $\beta_1$.

Table 6 reports the results of the cross sectional specification (5A) and the differenced specification (6) estimated over the years 2000 through 2004. Because we have repeated observations over individuals, we use a random effects specification. The results are remarkably consistent with the cross country findings in Table 4 and the OLS and IV estimates using Russian data in Table 5. When computer use is treated as exogenous, the estimated return is 0.17 and is highly significant. Similar qualitative results were obtained when we estimated the cross sectional relationship for individual years. The corresponding estimates in Tables 4 and 5 vary between 0.23 and 0.26 and are also highly significant.

The first differenced estimates divide the workers into four groups, those using computers in both years (Yes, Yes); those who never use computers (No, No); those who go from nonuse to use (No, Yes); and those who stop using computers (Yes, No). Using those who never use computers as a reference group, we would expect a positive coefficient on (No, Yes) and a negative coefficient on (Yes, No) if computer use at work raises earnings. We get that pattern, but the coefficients are statistically insignificant. When we estimate the equation for a specific year, the coefficient on (No, Yes) is only positive and significant in one of the four years. The IV estimates of the effect of computer use on earnings in Table 4 are all negative and insignificant, while the IV estimate of the impact of computer use on earnings in Russia in Table 5 is positive but insignificant. Roughly 12% of the sample are switchers, with half of these entering jobs with computers and half leaving jobs with computers.

The results in Table 6 buttress our earlier conclusions from Tables 4 and 5 that the apparent positive effect of computers on earnings in transition economies are due to highly productive workers being attracted to jobs involving computer use and not to a causal positive effect of computers on earnings. Correcting for nonrandom sorting of workers into the group using computers at work reduces the estimated return to computer use and in no case is the estimated return statistically significant.

## VII. Conclusions

The digital divide in transition economies is driven by the same factors (age, education, urban residence, information technology infrastructure) that are important in established market economies. In addition, ability to speak English and other G7 languages have a particularly strong effect on computer adoption, presumably because these language skills are complementary with computer use, given the preponderance of web sites written in English. An additional source of interest in computer usage in transition economies is that the Internet offers access to external sources of information on politics, business, culture, and science: information that is regarded as more reliable than that provided by domestic state-run media.

Computers and Internet connections are very expensive relative to per capita incomes in many transition economies. Consequently, home ownership of computers is relatively rare and most computer users access computers at work. Because competitive firms have to reduce the wages they offer workers to take into account these high usage costs, wage differences between computers users and nonusers are reduced in transition economies and they could even favor nonusers if workers get utility from using computers on the job. In our samples, it appears that the higher average pay for workers using computers in transition economies is attributable to the fact that computer users are drawn from the group of workers with atypically high unobserved ability and not to the computer use *per se*.

Note that if the cost of computer use falls in the future, wage differentials favoring computer users may yet appear in these transition economies. As pointed out by a referee, the high costs could be due to monopoly pricing or competitive pricing of naturally occurring high costs. The possible policy implications are not the same, as the government may wish to regulate prices or invite foreign competition in the former case, but it may need to decide whether intervention is even warranted in the latter.

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**Table 1 Summary information for different sub samples of working adults**

| | All working individuals aged 18-65 (n=5382) | | All working males aged 18-65 (n=2884) | | All working individuals aged 18-65 in households with one or two occupants (n=1066) | |
|---|---|---|---|---|---|---|
| | Mean | Std dev | Mean | Std dev | Mean | Std dev |
| **DEPENDENT VARIABLES** | | | | | | |
| **Use computer at** | | | | | | |
| home | 0.04 | 0.19 | 0.04 | 0.21 | 0.04 | 0.20 |
| work | 0.13 | 0.33 | 0.12 | 0.32 | 0.15 | 0.36 |
| school | 0.02 | 0.15 | 0.21 | 0.14 | 0.02 | 0.14 |
| Friends /relatives | 0.03 | 0.18 | 0.04 | 0.19 | 0.03 | 0.18 |
| | | | | | | |
| Income (dollars) | 101.02 | 87.81 | 105.17 | 84.08 | 86.08 | 68.9 |
| Income (log) | 4.26 | 0.92 | 4.32 | 0.91 | 4.13 | 0.89 |
| **INDEPENDENT VARIABLES** | | | | | | |
| **HUMAN CAPITAL** | | | | | | |
| Age | 39.30 | 10.85 | 39.08 | 11.12 | 44.13 | 12.33 |
| Education | 12.62 | 2.73 | 12.44 | 2.75 | 12.75 | 2.99 |
| English | 0.11 | 0.31 | 0.10 | 0.30 | 0.12 | 0.32 |
| G7 Language | 0.10 | 0.30 | 0.08 | 0.28 | 0.09 | 0.28 |
| Russian | 0.69 | 0.46 | 0.69 | 0.46 | 0.73 | 0.44 |
| **DEMOGRAPHICS** | | | | | | |
| Male | 0.54 | 0.50 | 1.00 | 0.00 | 0.44 | 0.50 |
| Urban | 0.64 | 0.48 | 0.61 | 0.49 | 0.75 | 0.43 |
| Household Size | 3.83 | 1.76 | 4.04 | 1.90 | 1.76 | 0.42 |
| Never married | 0.12 | 0.32 | 0.12 | 0.33 | 0.17 | 0.37 |
| **INTEREST IN** | | | | | | |
| Politics | 1.90 | 0.78 | 1.99 | 0.76 | 1.86 | 0.79 |
| Science | 1.91 | 0.72 | 1.94 | 0.74 | 1.82 | 0.70 |
| **INFRASTRUCTURE** | | | | | | |
| Local service | 0.10 | 0.11 | 0.09 | 0.11 | 0.11 | 0.12 |

## Table 2 :Summary information for all working households by country

| | Armenia N=(296) | Belarus (N=907) | Bulgaria (N=598) | Georgia (N=275) | Moldova (N=314) | Romania (N=637) | Russia (N=840) | Ukraine (N=676) | Uzbekistan (N=839) |
|---|---|---|---|---|---|---|---|---|---|
| **DEPENDENT VARIABLES** | | | | | | | | | |
| **Use computer at** | | | | | | | | | |
| home | 0.02 | 0.02 | 0.06 | 0.01 | 0.02 | 0.11 | 0.06 | 0.03 | 0.01 |
| work | 0.06 | 0.12 | 0.16 | 0.05 | 0.08 | 0.16 | 0.19 | 0.16 | 0.05 |
| school | 0.01 | 0.02 | 0.03 | 0.01 | 0.02 | 0.02 | 0.04 | 0.02 | 0.04 |
| Friends /relatives | 0.01 | 0.05 | 0.03 | 0.02 | 0.03 | 0.03 | 0.04 | 0.05 | 0.00 |
| Income (dollars) | 56.60 | 124.13 | 163.77 | 80.70 | 29.12 | 148.81 | 104.58 | 51.08 | 81.00 |
| Income(log) | 3.71 | 4.71 | 5.00 | 3.84 | 2.93 | 4.77 | 4.38 | 3.69 | 4.10 |
| **INDEPENDENT VARIABLES** | | | | | | | | | |
| **HUMAN CAPITAL** | | | | | | | | | |
| Age | 40.76 | 39.69 | 40.84 | 41.47 | 41.37 | 37.73 | 40.68 | 39.67 | 35.29 |
| Education | 13.02 | 12.58 | 12.48 | 13.96 | 12.04 | 12.75 | 12.58 | 13.12 | 11.94 |
| English | 0.14 | 0.09 | 0.14 | 0.13 | 0.04 | 0.28 | 0.05 | 0.12 | 0.05 |
| G7 Language | 0.06 | 0.08 | 0.13 | 0.09 | 0.11 | 0.29 | 0.04 | 0.09 | 0.03 |
| Russian | 0.89 | 0.76 | 0.27 | 0.86 | 0.97 | 0.04 | 1.00 | 0.89 | 0.70 |
| **DEMOGRAPHICS** | | | | | | | | | |
| Male | 0.54 | 0.51 | 0.52 | 0.51 | 0.57 | 0.57 | 0.50 | 0.49 | 0.62 |
| Urban | 0.68 | 0.72 | 0.81 | 0.48 | 0.42 | 0.67 | 0.77 | 0.64 | 0.39 |
| Household Size | 4.33 | 3.31 | 3.58 | 4.38 | 3.74 | 3.53 | 2.97 | 3.57 | 5.57 |
| Never married | 0.19 | 0.11 | 0.14 | 0.19 | 0.06 | 0.15 | 0.10 | 0.09 | 0.09 |
| **INTEREST IN** | | | | | | | | | |
| Politics | 1.66 | 1.87 | 1.88 | 2.00 | 1.61 | 1.52 | 1.84 | 2.11 | 2.29 |
| Science | 1.88 | 1.77 | 1.68 | 2.19 | 1.79 | 1.84 | 1.76 | 2.04 | 2.33 |
| **INFRASTRUCTURE** | | | | | | | | | |
| Local service | 0.01 | 0.07 | 0.21 | 0.04 | 0.06 | 0.21 | 0.04 | 0.16 | 0.03 |

**Table 3: Probit estimates of the determinants of use of computer at work for working adults**

| | All workers 18-65 | Working males 18-65 | Workers 18-65 in households with one or two occupants |
|---|---|---|---|
| **HUMAN CAPITAL** | | | |
| Age/10 | -0.02** | -0.02** | -0.02** |
| | (5.47) | (4.33) | (3.61) |
| Education | 0.02** | 0.02** | 0.03** |
| | (15.67) | (10.99) | (8.44) |
| English | 0.11** | 0.10** | 0.14** |
| | (6.64) | (4.46) | (3.20) |
| G7 Language | 0.03* | 0.02 | 0.03 |
| | (2.17) | (1.47) | (0.86) |
| Russian | 0.02• | 0.02 | 0.05* |
| | (1.77) | (1.37) | (2.20) |
| **DEMOGRAPHICS** | | | |
| Male | -0.01 | | -0.02 |
| | (1.78) | | (1.26) |
| Urban | 0.05** | 0.01 | 0.03 |
| | (4.97) | (1.01) | (1.49) |
| Household Size | -0.00 | -0.02 | 0.02 |
| | (1.16) | (-0.78) | (1.08) |
| Never married | -0.00 | 0.02 | -0.02 |
| | (0.20) | (0.68) | (0.03) |
| **INTEREST IN** | | | |
| Politics | 0.01** | 0.01• | 0.03* |
| | (2.61) | (1.80) | (2.37) |
| Science | 0.01• | 0.00 | 0.01 |
| | (1.66) | (0.61) | (0.89) |
| **INFRASTRUCTURE** | | | |
| Local service | 0.15** | 0.21** | 0.11 |
| Joint significance test of interest in politics and science($\chi^2$) | 13.05* | 4.64• | 8.24* |
| **Log Likelihood** | -1544.54 | -742.27 | -337.11 |
| **Pseudo $R^2$** | 0.24 | 0.28 | 0.26 |
| **N** | 5382 | 2884 | 1066 |

Note : Values reported are the estimated marginal effects. Specification also included dummy variable controls for country and broadly-defined industries (manufacturing, education, sales and services) as well as dummy variables for divorced, widowed, and separated.
z scores given in parenthesis. ** significant at the 1st percentile. * significant at the 5th percentile. · significant at the 10th percentile.

**Table 4 OLS and Instrumental Variables regressions of log household income for working adults**

| | Total Households | | Working Males | | Working households with one or two occupants | |
|---|---|---|---|---|---|---|
| | OLS | IV | OLS | IV | OLS | IV |
| **HUMAN CAPITAL** | | | | | | |
| Computer Use at work | 0.23** | -0.21 | 0.24** | -0.19 | 0.27** | -0.20 |
| | (7.95) | (1.22) | (5.77) | (1.00) | (4.62) | (0.78) |
| Age /10 | -0.30** | -0.30** | 0.30** | -0.03** | -0.05** | -0.50** |
| | (4.24) | (4.49) | (3.70) | (3.96) | (4.50) | (4.80) |
| ($Age^2$/10) | -0.00** | 0.00** | 0.00** | 0.00** | 0.01** | 0.01** |
| | (4.26) | (4.42) | (3.76) | (3.95) | (4.27) | (4.39) |
| Education | 0.06** | 0.07** | 0.05** | 0.07** | 0.05** | 0.07** |
| | (15.63) | (9.74) | (10.67) | (8.95) | (6.87) | (5.35) |
| English | 0.09** | 0.17** | 0.10* | 0.19** | 0.14* | 0.24* |
| | (2.94) | (4.15) | (2.13) | (3.15) | (2.00) | (2.49) |
| G7 language | 0.10** | 0.12** | 0.12* | 0.14** | 0.24** | 0.26** |
| | (3.25) | (3.96) | (2.56) | (3.02) | (3.18) | (3.32) |
| Russian | 0.02 | 0.03 | -0.04 | -0.03 | -0.07 | -0.05 |
| | (0.86) | (1.17) | (0.95) | (0.92) | (1.09) | (0.93) |
| **DEMOGRAPHICS** | | | | | | |
| Male | 0.10** | 0.10** | | | 0.19** | 0.18** |
| | (5.37) | (5.25) | | | (4.45) | (4.14) |
| Urban | 0.13** | 0.15** | 0.16** | 0.16** | 0.21** | 0.23** |
| | (5.19) | (5.43) | (4.40) | (4.65) | (3.65) | (3.67) |
| Household size | 0.08** | 0.08** | 0.07** | 0.07** | 0.18** | 0.19** |
| | (14.02) | (13.19) | (9.55) | (8.68) | (3.35) | (3.27) |
| **INFRASTRUCTURE** | | | | | | |
| Local service | 1.18** | 1.30** | 1.07** | 1.24** | 0.54* | 0.60* |
| | (9.23) | (9.04) | (5.71) | (6.59) | (2.24) | (2.17) |
| **$R^2$** | 0.53 | 0.52 | 0.53 | 0.52 | 0.52 | 0.51 |
| **N** | 5363 | 5363 | 2875 | 2875 | 1065 | 1065 |
| Overidentification test of restriction on interest in politics and science($\chi^2$) | 4.83* | | 2.30 | | 1.07 | |

Notes : Specification also included dummy variable controls for country and broadly-defined industries (manufacturing, education, sales and services) as well as dummy variables for divorced, widowed, and separated. Bootstrapped z scores standard errors reported in parenthesis for IV estimates. ** significant at the $1^{st}$ percentile. * significant at the 5th percentile.
· significant at the $10^{th}$ percentile
.

**Table 5 OLS and Instrumental Variables regressions of log household income for working adults (selected countries).**

| | Belarus | Bulgaria | Romania | Russia | Ukraine | Uzbekistan |
|---|---|---|---|---|---|---|
| **COMPUTER ADOPTION EQUATION[a]** | | | | | | |
| Age/10 | -0.19** | -0.11 | -0.25• | -0.10 | -0.10 | -0.14 |
| | (-2.84) | (-1.28) | (-1.72) | (-1.63) | (-1.53) | (-0.75) |
| Education | 0.20** | 0.23** | 0.26** | 0.20** | 0.16** | 0.09** |
| | (7.20) | (7.27) | (6.76) | (8.18) | (5.56) | (2.49) |
| English | 0.41* | 0.71** | 0.83** | 0.78** | 0.59** | 0.47 |
| | (2.30) | (3.68) | (4.60) | (3.38) | (3.39) | (1.62) |
| Urban | 0.25 | 0.69 | 0.74 | 0.43* | 0.53** | 0.11 |
| | (0.83) | (1.40) | (0.59) | (2.26) | (2.76) | (0.53) |
| **Interest in** | | | | | | |
| Politics | 0.10 | 0.10 | 0.19• | 0.07 | 0.02 | 0.14 |
| | (1.06) | (0.85) | (1.66) | (0.82) | (0.20) | (0.89) |
| Science | -0.05 | 0.23• | 0.15 | -0.02 | 0.22• | 0.25 |
| | (-0.51) | (1.95) | (1.26) | (-0.82) | (1.92) | (1.45) |
| Joint significance test of interest In politics and science($\chi^2$) | 1.19 | 6.16* | 5.67* | 0.66 | 5.07• | 4.52• |
| **DIGITAL DIVIDE** | | | | | | |
| Percentage of Gap explained by | | | | | | |
| Human capital | -0.46 | -1.34 | 2.40 | -0.79 | 2.11 | -2.53 |
| Demographics | 0.92 | 1.06 | 0.31 | 1.57 | 0.37 | -2.90 |
| Job Sector | 0.09 | 0.03 | 0.62 | -0.11 | -0.27 | 0.06 |
| Infrastructure | -0.62 | 2.25 | 2.35 | -1.10 | 1.29 | -1.40 |
| $\overline{X_i} - \overline{X_T}$ : Mean difference in adoption rates[c] | 0.00 | 3.14 | 3.28 | 5.99 | 3.84 | -7.30 |
| **LOG EARNINGS EQUATION[b]** | | | | | | |
| Computer use at work (OLS) | 0.16** | 0.07 | 0.25** | 0.23** | 0.33** | 0.15 |
| | (3.14) | (1.30) | (3.31) | (3.60) | (4.47) | (1.53) |
| Computer use at work(IV) | -0.70* | -0.03 | -0.10 | 0.09 | -0.32 | -0.15 |
| | (-2.32) | (-0.13) | (-0.41) | (0.25) | (-0.75) | (-0.28) |
| N | 894 | 592 | 637 | 839 | 676 | 839 |
| Overidentification test of restriction on interest in politics and science ($\chi^2$) | 0.09 | 0.06 | 0.06 | 0.08 | 0.07 | 0.08 |

[a] Specification also included all the other variables included in Table 3
[b] Specification also included all the other variables included in Table 4
[c]Difference between mean adoption rate for individual countries and mean adoption rate for all countries combined

Notes : z scores reported in parenthesis. ** significant at the 1st percentile. * significant at the 5th percentile.
· significant at the 10th percentile

**Table 6: Random effects regressions of log earnings in levels and differences using the Russian Longitudinal Monitoring Survey, 2000-2004**

| | **Estimation** | | **Summary information** | |
|---|---|---|---|---|
| | Levels | First difference | Levels Mean | First difference Mean |
| **DEPENDENT VARIABLE** | | | | |
| Log of wages | | | 7.79 | 0.30 |
| | | | (0.93) | (0.68) |
| **INDEPENDENT VARIABLES** | | | | |
| **Computer use at work** | 0.17** | | 0.25 | |
| | (0.03) | | (0.43) | |
| Yes in 1, Yes in 2 | | -0.01 | | 0.18 |
| | | (0.03) | | (0.37) |
| Yes in 1, No in 2 | | -0.03 | | 0.08 |
| | | (0.04) | | (0.27) |
| No in 1, Yes in 2 | | 0.02 | | 0.05 |
| | | (0.04) | | (0.21) |
| No in 1, No in 2 | | reference | | 0.69 |
| | | | | (0.46) |
| Age/10 | -0.00 | -0.21* | 41.97 | 41.97 |
| | (0.17) | (0.01) | (10.36) | (10.36) |
| Grades of school completed | | 0.01 | | 9.60 |
| | | (0.01) | | (1.05) |
| Less than grade 7 | reference | | 0.02 | |
| | | | (0.13) | |
| Grade 8 | 0.23* | | 0.22 | |
| | (0.11) | | (0.42) | |
| Grade 9 | 0.24* | | 0.06 | |
| | (0.12) | | (0.23) | |
| Grade 10 | 0.26* | | 0.56 | |
| | (0.11) | | (0.50) | |
| Grade 11 and greater | 0.17 | | 0.15 | |
| | (0.11) | | (0.35) | |
| Female | -0.43** | 0.03 | 0.57 | 0.57 |
| | (0.02) | (0.02) | (0.49) | (0.49) |
| **$R^2$** | 0.29 | 0.02 | | |
| **N** | 6235 | 5000 | 6235 | 5000 |

Notes: Standard errors reported in parenthesis for random effects estimates. Standard deviations reported in parenthesis for variable means. ** significant at the 1st percentile. * significant at the 5th percentile

## Endnotes

[1] See Katz and Autor (1999) for a comprehensive review of the changes in inequality and the explanations for those changes for OECD countries. More computer intensive sectors employ educated workers in greater proportions (Doms, Dunne and Troske(1997); Autor, Katz and Krueger, 1998) and have faster wage and productivity growth (Dunne et al, 2004).

[2] Krueger's (1993) analysis of U.S. data; followed by Entorf et al (1999) for France; Liu, Tsou and Hammitt (2004) for Taiwan; Dolton and Makepiece (2004) for England ; Oosterbeek (2004) for the Netherlands; Krashinsky (2004) for the U.S.; and Dostie, Jayaraman and Trépanier (2006) for Canada; have found least squares estimates of returns to computer use on the job to be large and positive with an average of about 20%. All but the first imposed corrections for possible endogeneity or unobserved heterogeneity. Estimated returns with controls are considerably smaller, ranging from 2-10% but are generally still positive and statistically significant.

[3] See Oliner and Sichel (200), Röller and Waverman (2001), Jorgenson (2001).

[4] Piatkowski(2004) presents evidence that links information technologies with accelerated growth in Central Europe and, to a lesser extent, Eastern Europe, but the evidence includes only a very few countries and time periods.

[5] Based on 2001 World Bank data on per capita gross national income and monthly off-peak Internet service charges.

[6] See Chinn and Fairlie (2004) and Dasgupta, Lall and Wheeler for cross-country estimation of factors affecting IT use.

[7] With Internet access individuals can also discharge a part of their job-related work from home (for example, checking and responding to emails), which allows them to spend more time with family that many individuals may find desirable.

[8] The formal derivation of these results is available in an theoretical appendix

[9] If equation (3') is approximated by a linear probability model, we can estimate (3') and (4) simultaneously (Wooldridge 2002; Gujarati, 2003).

[10] We explored the use of ordered probit for individual countries and generated similar results. However, this proved impractical in the sample pooled across countries because the income ranges differed across countries. There was no obvious way to accommodate overlapping pay ranges in the pooled sample using ordered probit.

[11] The quadratic form of the age variable was not statistically significant.

[12] All the earnings functions were reestimated using degree dummies rather than years of schooling and using potential experience = age – education -6 rather than age. Conclusions are not sensitive to these differences.

[13] In the studies cited in footnote 2, returns to computer use varied from 10-33% when computer usage is treated as exogenous.

[14] We tested the overidentification restriction that the taste for information measures can be excluded from the earnings equation. We could only weakly accept the null hypothesis that the two measures do not enter the earnings function in the full sample. In all other subsamples, the null hypothesis could not be rejected at even the $10^{th}$ percentile.

[15] Very similar conclusion are obtained when we treat computer adoption as linear and estimate equations (3') and (4) simultaneously. However, the estimates are less stable and the standard errors are much larger.

[16] The relevant studies are cited in footnote 2.

[17] Note that if workers have strong enough tastes for working with computers, the wage differential between jobs with and without computers could even reverse with workers accepting lower wages for the perquisite of using a computer on the job.

# Theory Appendix to "Computer Adoption and Returns in Transition"

## 1 The model

The model consists of $N$ small open economies indexed by $j \in \{1, 2.., N\}$. In each economy, there is an overlapping generations of individuals who live for two periods; in each period a continuum of individuals is born. In addition, there is a continuum of two types of firms. Both types of firms produce a single homogenous good. While type I firms use labor only, type II firms combine each worker with a computer to produce output. The primitives and the problems of each entity is described below.

The small open economy assumption implies that agents can borrow and lend freely at a gross interest rate $R$ determined in the world markets.[1]

To ease notation, we avoid time subscripts below since the choice problem of all generations is identical.

### 1.1 Individuals

An individual indexed by $i$ is identified by a pair $\{\xi_i, \tau_i\}$, where $\xi_i$ denotes her innate ability to learn, and $\tau_i$ is a stand-in for her desire to be up-to-date with information/computer technology and/or her preference for technological services such as the information that is accessible through the Internet (which is distinct from consumption of homogenous goods). We assume that $\xi_i$ and $\tau_i$ are jointly distributed over support $\left[\underline{\xi}, \overline{\xi}\right]$ and $[1, \overline{\tau}]$ with CDF (PDF) given by $G(\xi, \tau)$ $(g(\xi, \tau))$. An individual knows her $\xi$ and $\tau$. Her lifetime utility is given by

$$U = \ln c_{iy} + \rho \ln c_{io} + C_i \ (1 + \rho) \ \ln \tau_i \tag{1}$$

where $c_{iy}$ and $c_{io}$ denote the consumption of homogenous goods in her young and old age, respectively. The variable $C_i$ is a computer adoption variable takes a value of either 1 or 0; it is 1 if the individual adopts computer, 0 otherwise. Thus, the individual can enjoy computers and its services only if her adoption choice is unity. On the other hand, $c_{iy}$ and $c_{io}$ are continuous variables.

[1] The structure of financial markets in a closed economy can be easily endogenized by having agents live for three periods, and by modifying their human capital profile to ensure that agents borrow (save) in their first (second) period of life. This will unnecessarily complicate the analysis without yielding any further insights.

An individual is endowed with a unit of time in both periods. In the first period she has "raw" human capital that equals her unit time endowment, and she can only work in the type I firm at a wage rate $\bar{w}$. In the first period, however, she can educate herself by investing $H_i$ in education that increases her human capital (effective labor) to $h(\xi_i, H_i) > 1$. It is assumed that an individual's human capital is perfectly observable to the firms.

With enhanced human capital, the wage she can earn in a type I firm equals $\bar{w}\ h(\xi_i, H_i)$. Alternatively, she can train herself in computer/information technology that enables her to not only enjoy its services, but also qualifies her to work in a type II firm that offers a wage proportional to $h(\xi_i, H_i)$ (more of this below). However, learning computer/information technology costs $k(\xi_i, H_i)$.

***Assumptions*** It is assumed that

$$h_1 > 0, h_{22} < 0; h_2 > 0;\ h_{12} \geq 0. \tag{2}$$

The first set implies that human capital is increasing in education but with diminishing returns. Next, the higher the innate ability, the higher is the human capital for a given amount of education. Finally, the returns to education are non-decreasing in an agent's innate ability.

We also assume

$$k_1 < 0, k_{22} > 0; k_2 < 0;\ k_{12} = 0. \tag{3}$$

The first set implies that the cost of adopting computer/information technology is decreasing and convex in the amount of education. Next, it is decreasing in the individual's innate ability. The last assumption on the separability of the cost function in $\xi_i$ and $H_i$ is not necessary and is merely done for the sake of analytical simplicity.

It bears emphasis that the cost function $k$ can be potentially location-specific. In particular, a location with poorer infrastructure is likely to have a higher cost. For simplicity, however, we relegate the location-specific cost differences to the firms' problem below.

## 1.2 Firms

All firms are perfectly competitive. A type I firm uses a unit of human capital to produce a unit of output. Perfect competition then implies that $\bar{w} = 1$.

Type II firms combine each worker with a computer/IT terminal to produce output. These terminals enhance labor productivity: each unit of human capital produces $\eta > 1$ unit of output. However, setting up each terminal costs $f_j$ per period, where the subscript $j$ captures the notion that the costs are location-specific: a location with a poorer infrastructure entails a higher cost. Under perfect competition, an individual with human capital $h(\xi_i, H_i)$ is offered a wage that equals $\eta\ h(\xi_i, H_i) - f_j$.

### 1.3 The household's problem

Given the wage structure, we now solve the problem for an individual located in location 1. To ease notation, we drop subscript $j$ below; the solution can be easily applied to any location.

The problem of an agent $i$ is

$$\max_{H_i, c_{iy}, c_{io}, C_i \in \{0,1\}} \{\ln c_{iy} + \rho \ln c_{io} + C_i\ \ (1+\rho)\ \ \ln \tau_i\} \tag{4}$$

subject to

$$\begin{aligned} c_{iy} + H_i + C_i\ k(\xi_i, H_i) &= 1 + x_i &(5a)\\ c_{io} + R\ x_i &= C_i\,(\eta\ h(\xi_i, H_i) - f_j) + (1 - C_i)\, h(\xi_i, H_i) &(5b) \end{aligned}$$

where $x_i$ denotes an individual's borrowing when young. The LHS (RHS) in both (5a) and (5b) represent expenditures (resources available) to an agent in periods 1 and 2 respectively. As is standard, to avoid trends in variables, below we assume that $R = \rho^{-1}$.

As $C_i$ is a discrete choice, we first solve the household's choice problem separately for both $C_i = 0$ and $C_i = 1$. Then, we compare the resulting indirect utilities to identify households who choose to adopt or not to adopt computer/IT technology.

#### 1.3.1 $C_i = 0$

Here, by substituting (5a) and (5b) in (4), the household's problem can be reduced to

$$\max_{H_i, x_i} \left\{\ln(1 + x_i - H_i) + \rho\ \ln\left(h(\xi_i, H_i) - \rho^{-1}\ x_i\right)\right\} \tag{6}$$

The first order conditions are

$$\begin{aligned} \frac{1}{1 + x_i - H_i} &= \frac{\rho}{h(\xi_i, H_i) - \rho^{-1}\ x_i} h_2(\xi_i, H_i), &(7a)\\ \frac{1}{1 + x_i - H_i} &= \frac{1}{h(\xi_i, H_i) - \rho^{-1}\ x_i}. &(7b) \end{aligned}$$

Substituting (7b) in (7a) yields

$$h_2(\xi_i, H_i^*) = \rho^{-1} \tag{8}$$

where $H_i^*$ is the optimal level of education when $i$ does not train herself in computers. Finally solving for $x_i^*$ from (7b) and substituting it in (6) yields the indirect utility:

$$W^*(\xi_i) = (1+\rho)\left[\ln\left(1 - H_i^* + \rho\ h(\xi_i, H_i^*)\right) - \ln(1+\rho)\right]. \tag{9}$$

### 1.3.2 $C_i = 1$

Here, by substituting (5a) and (5b) in (4), the household's problem can be reduced to

$$\max_{H_i, x_i} \left\{\ln(1 + x_i - H_i - k(\xi_i, H_i)) + \rho\ \ln\left(\eta\ h(\xi_i, H_i) - f - \rho^{-1}\ x_i\right)\right\} \tag{10}$$

The first order conditions are

$$\frac{1 + k_2(\xi_i, H_i)}{1 + x_i - H_i - k(\xi_i, H_i)} = \frac{\rho}{\eta\ h(\xi_i, H_i) - f - R\ x_i}\eta\ h_2(\xi_i, H_i) \tag{11a}$$

$$\frac{1}{1 + x_i - H_i - k(\xi_i, H_i)} = \frac{1}{\eta\ h(\xi_i, H_i) - f - R\ x_i} \tag{11b}$$

Substituting (11b) in (11a) yields

$$\frac{\eta\ h_2(\xi_i, H_i^{**})}{1 + k_2(\xi_i, H_i^{**})} = \rho^{-1} \tag{12}$$

where $H_i^{**}$ is the optimal level of education when $i$ does train herself in computers. Finally solving for $x_i^{**}$ from (7b) and substituting it in (6) yields the indirect utility:

$$W^{**}(\xi_i) = (1+\rho)\begin{bmatrix} \ln\left(1 - H_i^{**} - k(\xi_i, H_i^{**}) + \rho\ \ (\eta\ h(\xi_i, H_i^{**}) - f)\right) \\ -\ln(1+\rho) + \ln\tau_i \end{bmatrix} \tag{13}$$

The following Lemma characterizes the choice of education as a function of innate ability. It also establishes

that for an individual the amount of education is higher if she also chooses to train in computers.

**Lemma 1** *Both $H_i^*$ and $H_i^{**}$are weakly increasing in $\xi_i$. Furthermore, $H^{**} > H^*$.*

**Proof.** See Section 2.1. ■

Intuitively, a higher innate ability increases the marginal product of education, and therefore the individual chooses a higher amount.[2] The second result $H^{**} > H^*$ is due to the feature that education not only increases one's human capital, but also reduces the cost of learning computers, as assumed in (3), in case the individual decides to train in computer/IT.

[2] Notice in particular that if $h_{12} > 0$, then both $H_i^*$ and $H_i^{**}$ are strictly increasing in $\xi_i$.

### 1.3.3 The choice of computer adoption

Comparing indirect utilities given by (9) and (13) implies that $C_i = 1$ if and only if

$$\begin{aligned}&\left(1 - \underbrace{H_i^{**} - k\left(\xi_i, H_i^{**}\right)}_{\text{cost of education and computer adoption}} + \underbrace{\eta\; h\left(\xi_i, H_i^{**}\right) - f}_{\text{earning in type II firm}}\right)\tau_i \\ \geq\;\; & 1 - \underbrace{H_i^{*}}_{\text{cost of education}} + \underbrace{h\left(\xi_i, H_i^{*}\right)}_{\text{earning in type I firm}} \end{aligned} \tag{14}$$

where $H_i^*$ and $H_i^{**}$ solve (8) and (12) respectively. Equation (14) leads to the following proposition.

**Proposition 1** *Given $\eta$ and $f$, the computer adoption rule for an individual $i$ is*

$$C_i = \begin{cases} 1, & \text{if } \;\xi_i \geq \hat{\xi}\left(\tau_i, \eta, f\right) \\ 0, & \text{if } \;\xi_i < \hat{\xi}\left(\tau_i, \eta, f\right) \end{cases}$$

*Moreover, $\hat{\xi}_1 < 0, \hat{\xi}_2 < 0, \hat{\xi}_3 > 0$.*

**Proof.** See Section 2.2. ■

The intuition behind the results stated in Proposition 1 is simple. Given the individual's preference for technology and the market wages on a job with computers, the higher her innate ability the more likely she is to adopt computers. The innate ability has a direct as well as indirect effect on computer learning. A higher ability facilitates a lower computer/IT learning cost. Second, a higher ability makes her achieve a higher level of education that also reduces her cost of technology adoption: an *indirect* effect.

The higher the individual's (hedonic) preference for technology, the lower is the ability at which she decides to adopt computers. A higher productivity in type II firms (i.e., jobs with computers) leads to higher equilibrium wages, thus inducing agents of lower abilities to also adopt computers and opt for working in type II firms. Similarly, a higher cost of IT investment by firms lowers equilibrium wages. Then, only relatively higher ability individuals will adopt and work on computer jobs. This is more likely to be observed in countries with relatively poorer infrastructure.

An interesting question is: can an individual with $\xi_i = \hat{\xi}$ be indifferent between the two choices even if her earnings in type II firms fall below that in type I firm? To answer this, first note from (14) that if she chooses to work in type II firms her education $H^{**}$ will be higher than had she chosen to work in a type I firm. In addition, she has to bear a cost of adopting computer/IT. However, if her preference for computer/IT services were strong enough, i.e., $\tau_i$ is large enough such that it compensates for her pecuniary loss, she would still choose to work in the type II firm. A similar argument holds for individuals with $\xi_i > \hat{\xi}$.

Thus, the model allows for instances where an individual chooses to work in type II firms even when wages are lower, or more specifically, even when wages net of cost of education and computer adoption are lower relative to the other alternative of working in type I firms.

# 2 Proofs

## 2.1 Proof of Lemma 1

**Proof.** Applying Implicit function theorem to (8) and (12) directly yields

$$\begin{aligned}\frac{dH_i^*}{d\xi_i} &= -\frac{h_{21}\left(\xi_i, H_i^*\right)}{h_{22}\left(\xi_i, H_i^*\right)} \geq 0 \\ \frac{dH_i^{**}}{d\xi_i} &= -\frac{\rho\ \eta\ h_{21}\left(\xi_i, H_i^{**}\right)}{\rho\ \eta\ h_{22}\left(\xi_i, H_i^{**}\right) - k_{22}\left(\xi_i, H_i^{**}\right)} \geq 0\end{aligned}$$

For the second part, assume $H^{**} \leq H^*$. Then, since $\eta > 1$ and $h_{22} < 0$, $\eta\ h_2\left(\xi_i, H_i^{**}\right) > h_2\left(\xi_i, H_i^*\right)$. Since the denominator in (12) is less than unity, $\frac{\eta\ h_2\left(\xi_i, H_i^{**}\right)}{1+k_2\left(\xi_i, H_i^{**}\right)} > h_2\left(\xi_i, H_i^*\right) = \rho^{-1}$, which contradicts (12). Hence, $H^{**} > H^*$. ■

## 2.2 Proof of Proposition 1

**Proof.** Fix $\tau_i, \eta$, and $f$. By Envelope Theorem the derivative of the LHS in (14) $-k_1\left(\xi_i, H_i^{**}\right) + \eta\ h_1\left(\xi_i, H_i^{**}\right) > 0$ and that of the RHS is $h_1\left(\xi_i, H_i^*\right) > 0$. Thus, both sides of (14) are increasing in $\xi_i$.

To prove the first part we need to show that $-k_1\left(\xi_i, H_i^{**}\right) + \eta\ h_1\left(\xi_i, H_i^{**}\right) > h_1\left(\xi_i, H_i^*\right)$. This is done by noting that $-k_1\left(\xi_i, H_i^{**}\right) > 0$; $h_{12} > 0$, and $H_i^{**} > H_i^*$ from Lemma 1.

The second set of results is obvious from (14). ■