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ABSTRACT

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Data from nine transition economies in Central and Eastern Europe are used to examine the role of computer adoption for returns to education. As in western economies, computers are adopted most heavily by young, educated, English-speaking workers with the best access to local telecommunications infrastructures. These same attributes have been associated with rising relative earnings in transition economies. Controlling for likely simultaneity between computer use and labor market earnings, we find much larger returns to individuals from computer adoption than have been found in established market economies. The large returns are explainable by the high cost of adoption and the scarcity of computer skills. As of 2000, only 14% had ever tried a computer. Consequently, despite much larger individual returns, computers are associated with an 8% increase in average incomes in the nine countries.

JEL Classification: O, P2, J31

Keywords: computer adoption, transition economies, earnings, returns, telecommunications

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I. Introduction

Starting in the 1980s, there was a general trend toward rising 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.[1] New technologies, particularly information technologies, have raised the productivity and/or lowered the cost of capital. 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.[2]

Transition economies have been characterized by rapidly increasing returns to education (Brainerd, 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.

Another characteristic of centrally planned economies was an underinvestment in certain segments of the economy, particularly in the consumer and service sectors of the economy. While the Soviet economy heavily invested in capital, those investments were heavily weighted toward military and heavy manufacturing and generated virtually no return (Easterly and Fischer, 1995). One area that was relatively underdeveloped was in telecommunications and other information technologies. Consequently, most of the formerly planned economies entered transition with poorly developed communications systems compared to the west. The lack of emphasis on consumer products also meant that relatively few citizens of the planned economies owned or even had ever worked on a personal computer.

Reluctance to expose state-run telecommunications monopolies to competition, whether from abroad or from domestic firms, has kept prices high and service quality low compared to prices in the west. Often, only corporate clients, banks, and foreign representative offices can afford these services. In Uzbekistan, for example, one hour of day time dial-up connection provided by the official telecommunications monopoly UzPAK costs 8% of the average monthly salary. One hour of night time dial-up service costs about half that, but still clearly unaffordable for the average citizen (Revin, 2001).

As late as 2002 after more than ten years of transition, 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. 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).

If information technologies are complementary with skill in transition economies, then computer skills may be earning a premium in the formerly planned economies. Furthermore if there is underinvestment in information technologies relative to their returns, then workers who get access to the rationed information technology may earn relative returns to computer use that are even larger than the returns earned by computer users in western economies. Furthermore, to the extent that it is the most educated that are using computers, some of the large increase in observed returns to education in the transition economies could be attributable to differential access to the use of information technologies between the most and the least skilled workers.

This study examines the role of computer usage on earnings in nine formerly planned economies: Belarus, Bulgaria, Georgia, Moldova, Romania, Russia, Ukraine, and Uzbekistan. We find evidence of large returns to computer use that are twice those found in studies in Europe or the United States. Controlling for likely simultaneity and measurement error in computer adoption makes the estimated returns even larger.

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 to use a computer if the expected net present value (ENPV) of computer adoption is greater than ENPV from not using a computer. At a given point in time, let the ENPV from computer adoption be approximated by

(1) $$V(C_{ij} = 1; Y_{ij}, H_{ij}, Z_{ij}, T_{ij}, \tau^{c}_{ij}),$$

where C_{ij} is a dummy variable indicating computer adoption by individual I in country j, Y_{ij} is income, H_{ij} is a vector of 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 of using a personal computer, and τ^{c}_{ij} is the hedonic returns to computer adoption. Similarly, ENPV of not adopting a computer is given by

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

The decision to adopt a computer depends on the relative magnitudes of the EPNV. Adoption probability can be written as

$$P(C_{ij} = 1) = P\{V(C_{ij} = 1; Y_{ij}, H_{ij}, Z_{ij}, T_{ij}, \tau^{c}_{ij}) - V(C_{ij} = 0; Y_{ij}, H_{ij}, Z_{ij}, T_{ij}) > 0\}.$$

Linearizing the EPNV functions, the probability of computer adoption will have the form

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

where the parameters, α_k, indicate the relative present value return to the k^{th} variable from using a computer versus not using a computer and ε_{ij} is an approximation error assumed to be normally distributed with mean zero and constant variance.[3] If $\alpha_k > 0$, then the k^{th} factor can be interpreted as being complementary with computer use.

Computer adoption can be viewed as an investment with current investment costs in training time and equipment purchases, which are expected to be rewarded with a future return in the form of higher labor market earnings. Past studies of computer adoption in western economies have generated consistent predictions about 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 other studies.

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).

In the absence of liquidity constraints, computer adoption would not be expected to vary with household income, Y_{ij}. However, it may be difficult for a household to borrow in order to purchase a computer, and in transition economies, cost of borrowing is likely to rise as household wealth or available collateral falls. Therefore, computer adoption is likely to increase with household income or wealth. Even in western economies where liquidity constraints should be less severe, there is a strong positive relationship between computer use and household income (Schirmer and Goetz, 1997; Fairlie ,2004).

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. For example, if DSL or cable high-speed internet connections are only available in metropolitan areas, rural internet use will require expensive satellite connections or poor quality dial-up service. Therefore, holding constant the overall level of development in the country, more widely available telecommunications infrastructure should increase adoption.

Computers are also complementary with many nonpecuniary uses. In particular, they improve information processing, so individuals interested in accessing current local or global political or societal information for nonbusiness purposes will have an incentive to adopt computers, even if the information has no direct economic return.

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

where the variables are defined as before and ξ_{ij} is a random error term. The coefficient, β_1, is interpretable as the rate of return from use of a computer.

III. Estimation strategy

If ξ_{ij} is uncorrelated with the regressors, then ordinary least squares estimation of (4) will yield unbiased estimates of β_1. However, if computer adoption depends on household wealth or income, as in the case of liquidity constraints for example, then computer adoption will depend on all of the determinants of income including ξ_{ij}. The correlation between C_{ij} and ξ_{ij} will cause bias in the least squares estimation of β_1 in (4). In particular, if higher income raises the probability of computer adoption and there are no other sources of bias in (4), we would expect positive values of ξ_{ij} to be positively correlated with C_{ij}, and so least squares estimates of β_1 would be biased upward.

On the other hand, β_1 will also be biased if C_{ij} is measured with error. If measurement error were the only source of bias, then β_1 will be biased toward zero. Our measure of C_{ij} may be measured with error for two reasons. First, the queston may be subject to recall bias because it is asked retrospectively (“Have you ever used a computer?”). Second, the question does not distinguish between using computers for work and using computers for consumption. Only the former has been found to affect earnings in previous studies. Because our empirical model emphasizes economic uses of the computer, predicted usage may more closely mimic the use of computers for business purposes. Note that both measurement error and endogeneity problems can be addressed by the same instrumental variable method. Note also that if both sources of error are important, we can no longer have unambiguous expectations regarding the direction of bias in the OLS estimates of β_1.

If equations (3) and (4) were linear, they could be estimated simultaneously or using two-stage least squares (Wooldridge 2000; Gujarati, 2003). However, 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). $\hat{C}_{ij}$ will be purged of the impact of Y_{ij} on C_{ij}, $\hat{C}_{ij}$ will be uncorrelated with ξ_{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).

To 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 are measures of T_{ij} and τ_{ij}^{c}. As we show below, our findings are robust to several alternative choices with regard to the specification of the instruments. In all specifications, the two-stage estimation yields larger values of β_1 than when C_{ij} is treated as exogenous, suggesting that measurement error in C_{ij} may be more important than endogeneity. However, in all cases, the estimates of β_1 are positive and significant, suggesting that computer usage does generate a significant return in transition economies.

IV. Data

This study utilizes data collected by the Intermedia Survey Institute based in Washington D.C. The data was collected in the nine transitional economies in Eastern Europe in the year

2000 through face-to-face interviews conducted through local agencies. Countries included Belarus, Bulgaria, Georgia, Moldova, Romania, Russia, Ukraine, and Uzbekistan. Useable sample sizes varied from 751 in Moldova to 2008 in Romania with most countries having between 1500 and 1800 observations. The pooled sample included 12795 observations.

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 service, 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.

Variable definitions and summary statistics for all the variables utilized in the study are presented in Table 1. The dependent variables in the analysis are a binary variable on computer use and the log of household 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.[4] We use the 2000 Purchasing Power Parity exchange rates to convert the various home currencies into US dollar equivalents.

Use of household income is not ideal because of the possibility of multiple earners in the household. 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, marital status). Second, we replicate all results using only the subsample of workers in one-person households so that household income can be equated with individual income. Qualitative results are virtually identical in the two samples, corroborating our results.

The explanatory variables are subdivided into six categories: demographic, sector of employment, attitudes towards information, language, local telecommunications infrastructure and country characteristics. Most are self-explanatory and do not require explanation. Our measures of T_{ij} include measures of overall development (GDP per capita) and the availability of telecommunications infrastructure (telephone lines per 100 inhabitants in the country and an index of available information technology in the local community). To avoid having local service availability merely proxy for more populous areas, we also include a dummy variable that indicates whether the individual resides in an urban area. Information on national teledensity was obtained from the International Telecommunications Union (ITU, 2001). We used measured GDP per capita in PPP dollars as reported in *The CIA World Factbook* 2002 . Availability of local telecommunications infrastructure was indicated by local access to cable television or satellite services. These services either are or potentially could be converted to provide local Internet access that dominates dial-up services. For all of these variables, better telecommunications infrastructure at the national or local level should lower the cost of computer use and/or make the computer more productive.

Our measures of τ_{ij}^{c} include measures of the importance the individual places on having current information on various topics (politics, foreign cultures, the economy and scientific or technological advances). Because computer technology aids information gathering and processing, individuals who place greater priority on having current information should be more motivated toward computer adoption.

Finally, the role of language in computer adoption may be important. English is complementary with computer use because 80 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 corroborated by the findings of Fairlie (2004). Our data set allows us to control for ability to speak English, other G7 languages, or Russian in addition to the local language of the country.

V. Determinants of computer adoption

The computer adoption equation (3) has interest on its own beyond its utility as a means of identifying computer adoption in equation (4). If there is a return to computer usage, adoption rates will identify winners and losers from improved availability of information technologies. Results of the probit estimation for the pooled sample for 9 countries are included in Table 2. Coefficient estimates were very similar across countries and so they are suppressed to save space.[5] To ease interpretation, the marginal effect of each variable on probability of computer adoption is also reported.

Human capital measures have a large effect on the probability of computer adoption. Age has a negative and significant effect on computer use, although the magnitude of the effect is small—roughly a three percentage point decrease for every 10 years of age. Every year of education increases the probability of computer use by 1.2 percentage points, roughly the same amount as a four year decrease in age. Relative to an individual with average education (11 years), a college graduate is 45% more likely to have used a computer. This skill technology complementarity has also been found in the U.S. and in other OECD countries (Katz and Autor, 1999; Autor et al.,1998).

Those who speak English are almost 9 percentage points more likely to use a computer, a huge effect compared to an average probability of 14% in the population as a whole. Those who speak other G7 languages are almost 3 percentage points more likely to use a computer, as are those who speak Russian. Clearly, language skills have a very large effect on computer adoption.

Single, never-married householders were particularly more likely to adopt, but adoption was otherwise not related to household structure. Urban residents were 3 percentage points more likely to use a computer. Men and women were equally likely to use computers.

Interest in information does appear to increase the hedonic return from computer use. The strongest effect is for those who have an interest in economics, both in terms of magnitude and significance. However, individuals interested in politics and science were also more likely to adopt, although the coefficients were only significant at the tenth percentile. Cultural interests did not spur individuals to use a computer. The joint test of significance of the information interest group strongly rejected the null hypothesis of no effect.

Infrastructure supporting information technologies is also very important.[6] Local access to satellite or cable service had a large impact on adoption. Those with local service were 5 percentage points more likely to adopt. Overall economic development also raises the probability of adoption by 5 percentage points when evaluated at sample means. National levels of teledensity did not have a large effect when local service was controlled. It is apparent that computer adoption is very sensitive to the availability of complementary infrastructure that make the computer more productive, particularly at the local level.

Overall, the determinants of computer adoption in these transition countries are very 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. The literal interpretation of the coefficients is that these same attributes are complementary with computer use so that the present value of computer adoption dominates avoidance for the young, educated, informed, multilingual residents of areas with access to local information technology services.

VI. Returns to computer adoption

In the second stage of our analysis, a Mincerian log earnings function supplemented by actual and predicted use of computers is estimated. The results for household income are presented in Table 3 and results for income for single individual households are presented in Table 4. Across all specifications, the earnings functions fit quite well with 36-44% of the variance explained by the model. Whether computer use is treated as exogenous or endogenous, its estimated coefficient is positive and significant. The magnitude of the computer use coefficient is larger in the instrumental variables estimates, suggesting that measurement error may be the bigger source of bias in the ordinary least squares estimates.

We used several alternative sets of exclusion restriction following the guidance from the theory that we should concentrate on measures of available technology T_{ij} and tastes τ^{c}_{ij}. The most plausible choices were to exclude local available complementary satellite and cable services (holding fixed the control for urban areas that would capture average earnings increases associated with population density) and/or to exclude the measures of interest in information. As it turns out, our results were not overly sensitive to the various exclusion restrictions that we tried. We report results from these two most plausible specifications.

The coefficient on education is not very sensitive to the inclusion or exclusion of computer use from the specification, implying that estimated returns to education have not been biased by missing controls for information technologies. Age and ability to speak English were very sensitive to the use of instruments. When computer use is treated as exogenous, an additional year of age or potential work experience implausibly lowers income. With the IV estimation, the effect turns positive with a 1-2% increase in income for every additional year, consistent with most earnings equations. English has a strong positive effect on earnings when computer use is excluded or treated as exogenous, but the effect disappears in the IV estimation. These findings are consistent with a presumption that young workers and those with English language ability are getting additional earnings from their increased propensity to use new information technologies and not from their youth or English language skills directly.

The other coefficient estimates were not particularly sensitive to the estimation method. In the Table 4 estimation, there was a strong return to speaking other G7 languages whether or not the individual used a computer. This could reflect the greater trade flows between the former Soviet states and Europe. Ability to speak Russian is detrimental to earnings, possibly reflecting the collapse of trade among the former Soviet states. It is also possible that ethnic Russians have experienced discrimination in the labor market.[7] Men and urban dwellers earn significantly higher incomes. Individuals with greater interest in news earned more with the exception of those atypically interested in economics, although the effect dissipates in the sample of single individuals.

The larger sample in Table 3 includes household income from other potential workers besides the respondent. We include many controls for the composition of the household to attempt to correct for biases associated with possible multiple earners. As an alternative, we replicated the estimation over a sample including only a single member households, and hence, only a single earner. The estimated coefficients were quite similar across the two samples, suggesting that the controls for household composition were successful in controlling from the possible biases associated with multiple earner households.

The exception is that the estimated returns to computer use are larger in the full sample. It is plausible that computer skills are shared among household members, and so households with returns from one worker who uses a computer are also getting returns from other members who use the computer. Consequently, the estimated returns to computer use from the sample of single householders are more reliable, and our discussion concentrates on those estimates.

The implied elasticity when computer use is treated as exogenous suggests that a 10% increase in the probability of computer adoption raises income by 0.4% in both the full and single samples, evaluated at the sample means. In the instrumental variables estimation, the elasticity rises to 0.11 in the full sample and to 0.08 in the single householder sample. When treated as exogenous, the magnitude of the coefficients suggest returns to computer use that are around 33%, roughly double the size of returns reported in the United States when computer use was treated as exogenous (Krueger, 1993). The implied returns in the instrumental variable regressions are even larger. Because so few have actually adopted the computer, however, the impact of computer use on average incomes is only 8%, evaluating the computer use effect at sample means.

There are two reasons why the individual returns to computer use would be much larger in transition than in western industrialized economies. First, computer skills and computer usage was artificially constrained in the planned system, and the level of usage is still very low in these countries relative to the level of development. The proportion who have ever used a computer varies from 4% in Armenia to 21% in Russia with an average of 14% across all nine countries. The proportion using a computer for work would be even smaller. Because of the great marginal expense of acquiring and using a computer relative to local incomes, the labor market has not adjusted rapidly to drive the returns lower. Second, the marginal returns have to be large to compensate for the extremely high marginal cost of computer use documented above. Finally, while these estimates (particularly the instrumented estimates) seem high, their qualitative interpretation that returns to computer use in transition economies are larger than in established market economies seems plausible.

We can illustrate the importance of telecommunications infrastructure for computer adoption and incomes across these countries as follows. Using the country averages for local service delivery and teledensity we use the estimates in Table 2 to generate the implied marginal computer adoption probability.[8] We then apply the marginal probability of adoption to the estimates in column 3 of Table 4 to generate an implied income return. This simulation is reported in the upper panel of Table 5. It is apparent that the current level of infrastructure is too small to have had a large effect on adoption or earnings across these countries. The largest effects are in Bulgaria and Romania where computer adoption is 2 percentage points greater and average incomes are 1% higher as a result of their information infrastructure. In contrast, Uzbekistan has almost no computer adoption related to its level of installed information technology. The average across all countries is a 1.2 percentage point higher level of computer use and 0.7% higher incomes. To put this in perspective, almost the same increases in computer adoption and income are due to current skills in English and other G7 languages. If one avenue for development in these countries is through increased use of computers, it may be less expensive to rapidly raise language skills (that may have a direct return as well as an indirect return through increased computer adoption) than to rapidly expand installation of information technology infrastructure.

VII. **Conclusions**

Incentives to adopt computers in transition economies are driven by the same factors (age, education, urban residence, information technology infrastructure) that have been found to be important in established market economies. In addition, ability to speak English and other G7 languages and having interest in current economic, political or scientific information are also important in transition economies. Individual who use computers in transition economies get marginal returns that are much larger than those earned in countries where adoption levels are much higher. The high costs of adoption and the relative scarcity of computer skills are apparently causes of those high returns.

Returns are high enough that they should be spurring considerable investment in computer training in these countries. However, the average adoption rate as of 2000 was only 14%. Nevertheless, that level of adoption is sufficiently large to suggest that computer use has increased average incomes by 8% across the 9 countries in the study. Policies regarding installation of information infrastructure have only a small role in spurring adoption – individual skills and personal interest in information have a greater influence on computer adoption.

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Table 1: Summary Statistics

	Variable Title	**Description**	Total (12795)	
			mean	s.d
Dependent Variables	C	Ever used computer? (1=yes,0=no)	0.14	0.35
	ln(Y)	Log of dollar value of personal income.	3.98	1.05
Human Capital	Age	Years of age	45.16	18.09
	Education	Years of education	11.12	3.49
Demographics	Male	Gender (1=male,0=female)	0.45	0.50
	Urban	Location (1=urban, 0=non urban)	0.58	0.49
	Household size	Number of people per household	3.58	1.90
	Married	Married (1=yes, 0 =no)	0.66	0.48
	Divorced	Divorced (1=yes, 0=no)	0.05	0.21
	Separated	Separated (1=yes, 0=no)	0.01	0.10
	Widowed	Widowed (1=yes, 0=no)	0.12	0.33
	Never married	Never married (1=yes, 0=no)	0.15	0.36
Sector	Agriculture	Occupation in agriculture (1=yes, 0=no)	0.07	0.26
	Manufacturing	Occupation in manufacturing (1=yes,0=no)	0.08	0.27
	Sales/service	Occupation in sales or service (1=yes,0=no)	0.10	0.30
Interests	Politics	Level of interest in local and international politics. Range: 3(very interested) to 1 (not very interested).	1.76	0.86
	Culture	Level of interest in other cultures. Range: 3(very interested) to 1 (not very interested).	1.35	0.75
	Economics	Level of interest in economics and business. Range: 3(very interested) to 1 (not very interested).	1.44	0.84
	Science	Level of interest in science and technology. Range: 3(very interested) to 1 (not very interested).	1.81	0.75
Language	English	Can you speak/read English (1=yes, 0=no)	0.09	0.29
	G7 language	Can you speak/read other G7 languages (1=yes, 0=no)	0.08	0.27
	Russian	Can you speak/read Russian (1=yes,0=no)	0.61	0.49
Infrastructure	Local service	Index of local availability of cable or satellite service	0.09	0.11
	Teledensity	Main telephone lines per 100 inhabitants (2001)	19.35	8.15
	GDP per capita	GDP per capita (2001) US $	5432.94	2223.63

Table 2: Probit estimates of the determinants of computer adoption

	Coefficient	$\frac{\partial F(X\beta)}{\partial X_k}$
HUMAN CAPITAL		
Age/10	-0. 352**	-0.031
	(0. 018)	
Education	0.136**	0.012
	(0.007)	
English	0.632**	0.086
	(0.047)	
G7 Language	0.291**	0.032
	(0.053)	
Russian	0.348**	0.029
	(0.049)	
DEMOGRAPHICS		
Male	0.003	0.000
	(0.036)	
Urban	0.342**	0.029
	(0.049)	
Household Size	-0.019	-0.002
	(0.012)	
Never married	0.313*	0.033
	(0.145)	
INTEREST IN		
Politics	0.048	0.004
	(0.027)	
Culture	-0.010	-0.001
	(0.031)	
Economics	0.205**	0.018
	(0.027)	
Science	0.050	0.004
	(0.029)	
INFRASTRUCTURE		
Local service	0.572**	0.050
	(0.207)	
GDP per capita/100	0.011**	0.001
	(0.001)	
Teledensity/100	0.470	0.041
	(0. 312)	
Constant	-3.308**	
	(0.204)	
Log Likelihood	-3353.15**	
Pseudo R^2	0.35	
N	12795	

Note : Specification also included dummy variable controls for broad industry of occupation and marital status described in Table 1.
Standard errors given in parenthesis. ** significantly different from zero at the 1 percent level. * significantly different from zero at the 5 percent level

Table 3: OLS and Instrumental Variables regressions of log household income (Total households)

	OLS	OLS	IV	IV
HUMAN CAPITAL				
Computer Use	0.301**		0.783**	0.864**
	(0.025)		(0.089)	(0.118)
Age /10	-0.007	-0.016**	0.008	0.020**
	(0.006)	(0.001)	(0.007)	0.008
Education	0.046**	0.049**	0.041**	0.050**
	(0.003)	(0.003)	(0.003)	(0.002)
English	0.173**	0.255**	0.044	0.027
	(0.029)	(0.028)	(0.038)	(0.043)
G7 language	0.046	0.071**	0.006	0.007
	(0.028)	(0.029)	(0.031)	(0.032)
Russian	-0.346**	-0.335**	-0.362**	-0.322**
	(0.016)	(0.016)	(0.017)	(0.016)
DEMOGRAPHICS				
Male	0.055**	0.056**	0.056**	0.073**
	(0.015)	(0.016)	(0.015)	(0.016)
Urban	0.325**	0.040**	0.303**	0.304**
	(0.017)	(0.017)	(0.017)	(0.017)
Household size	0.165**	0.164**	0.167**	0.172**
	(0.005)	(0.005)	(0.005)	(0.065)
INTEREST IN				
Politics	0.112**	0.110**	0.113**	
	(0.011)	(0.011)	(0.011)	
Culture	0.032**	0.029*	0.036**	
	(0.013)	(0.013)	(0.014)	
Economics	-0.027*	-0.015	-0.045**	
	(0.012)	(0.012)	(0.014)	
Science	0.094**	0.095**	0.092**	
	(0.012)	(0.013)	(0.011)	
INFRASTRUCTURE				
GDPpercapita/100	0.017**	0.017**	0.016**	0.015**
	(0.000)	(0.000)	(0.000)	(0.000)
National Teledensity/100	0.148	0.170	0.103	-0.062
	(0.130)	(0.131)	(0.114)	(0.118)
Constant	1.480**	1.382**	1.421**	1.636**
	(0.090)	(0.899)	(0.090)	(0.093)
R^2	0.37	0.37	0.37	0.36
N	12795	12795	12795	12795
Computer use elasticities	0.04		0.11	0.12

Note : Specification also included dummy variable controls for broad industry of occupation and marital status. Bootstrapped standard errors reported in parenthesis for IV estimates.** significantly different from zero at the 1 percent level. * significantly different from zero at the 5 percent level

Table 4: OLS and Instrumental Variables regressions of log household income (Single individuals)

	OLS	OLS	IV	IV
HUMAN CAPITAL				
Computer Use	0.286**		0.564**	0.447*
	(0.097)		(0.285)	(0.242)
Age /10	-0.002	-0.009	0.019**	0.018**
	(0.017)	(0.002)	(0.002)	(0.002)
Education	0.035**	0.037**	0.033**	0.042**
	(0.006)	(0.006)	(0.006)	(0.006)
English	0.110	0.201	0.025	0.039
	(0.112)	(0.108)	(0.173)	(0.162)
G7 language	0.328**	0.335**	0.306**	0.293**
	(0.100)	(0.099)	(0.093)	(0.087)
Russian	-0.259**	-0.259**	-0.260**	-0.217**
	(0.045)	(0.045)	(0.038)	(0.045)
DEMOGRAPHICS				
Male	0.269**	0.272**	0.271**	0.283**
	(0.047)	(0.047)	(0.047)	(0.052)
Urban	0.310**	0.317**	0.305**	0.319**
	(0.044)	(0.044)	(0.043)	(0.054)
INTEREST IN				
Politics	0.092**	0.086**	0.096**	
	(0.029)	(0.029)	(0.031)	
Culture	0.011	0.010	0.016	
	(0.037)	(0.037)	(0.037)	
Economics	-0.037	-0.025	-0.048	
	(0.037)	(0.036)	(0.041)	
Science	0.052	0.050	0.053	
	(0.035)	(0.035)	(0.037)	
INFRASTRUCTURE				
GDPpercapita/100	0.017**	0.018**	0.018**	0.018**
	(0.001)	(0.001)	(0.001)	(0.001)
National Teledensity/100	1.183**	1.217**	1.204**	1.200**
	(0.004)	(0.381)	(0.432)	(0.367)
Constant	1.074**	1.104**	0.975**	1.280**
	(0.158)	(0.158)	(0.191)	(0.209)
R^2	0.44	0.44	0.44	0.42
N	1312	1312	1312	1312
Computer use elasticities	0.04		0.08	0.06

Note : Specification also included dummy variable controls for broad industry of occupation. Bootstrapped standard errors are reported in parenthesis for IV estimates. ** significantly different from zero at the 1 percent level. * significantly different from zero at the 5 percent level

Table 5: Simulated Effects of Telecommunications infrastructure on computer adoption and income in 9 Transition Economies				
	A. Infrastructure			
Country	Local service	Teledensity	Computer Use	ln(Y)
Armenia	0.02	14	0.007	0.004
Belarus	0.06	30	0.015	0.009
Bulgaria	0.18	37	0.024	0.014
Georgia	0.06	13	0.008	0.005
Moldova	0.06	15	0.009	0.005
Romania	0.23	18	0.019	0.011
Russia	0.04	24	0.012	0.007
Ukraine	0.03	21	0.010	0.006
Uzbekistan	0.03	6	0.004	0.002
Average	0.09	19	0.012	0.007
	B. Language			
Country	English	G7 Language	Computer Use	ln(Y)
Armenia	0.1	0.05	0.010	0.006
Belarus	0.08	0.07	0.009	0.005
Bulgaria	0.09	0.09	0.011	0.006
Georgia	0.12	0.09	0.013	0.007
Moldova	0.04	0.08	0.006	0.003
Romania	0.19	0.18	0.022	0.012
Russia	0.04	0.03	0.004	0.002
Ukraine	0.09	0.08	0.010	0.006
Uzbekistan	0.02	0.04	0.003	0.002
Average	0.09	0.08	0.010	0.006
Source: Authors' computations based on information in Tables 1, 2, and 4				

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.

[2] There is not universal agreement that information technologies are responsible for the rising returns to education in OECD countries. While 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), but it is not clear if these changes are due to computer intensity or other factors associated with hiring more educated labor. Several papers (Krueger, 1993; Liu, Tsou and Hammitt, 2004; Dolton and Makepiece, 2004; Oosterbeek, 2004) have found positive and significantly higher wages for workers who use computers at work across several countries, but others (Entorf and Kramarz, 1996; Krashinsky, 2004) find the results are sensitive to the imposition of statistical controls for endogeneity and individual heterogeneity.

[3] If ε_{ij}^{c} is the error from the linear approximation to (1), and ε_{ij}^{0} is the error from the linear approximation to (2), then $\varepsilon_{ij} = \varepsilon_{ij}^{c} - \varepsilon_{ij}^{0}$.

[4] 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. In addition, the pooled sample allows us to assess the importance of variation in access to telecommunications infrastructure across countries for adoption and earnings.

[5] Although the global test of equality of all coefficients rejected the null hypothesis of equality, coefficients were quite similar across countries in sign and significance. In all countries, age had a significant negative effect on the probability of computer adoption while education, availability of local telecommunications infrastructure and English language ability increased computer use. Interest in economic news and other language ability (Russian or other commercial languages) also increased the probability of adoption in all countries, although the coefficients were not always significant. The model fits similarly as well, with Pseudo R^2 varying from 0.3 to 0.5. See Kuku (2003) for details.

[6] Chinn and Fairlie (2004) found that telecommunication infrastructure helped to explain variation in computer and Internet usage across 161 countries over the 1999-2001 period.

[7] Ethnic Russians faced wage and employment discrimination in the early Estonian transition (Noorkoiv et al, 1998).

[8] We do not use GDP per capita as it would represent an overall level of development and not just information technology.