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Abstract

This dissertation studies the adoption and usage patterns of information communication technologies and how the spread of these technologies affects labor market outcomes. I approach this question in three ways. First, I analyze the effects of the expansion of broadband Internet access from 1999 to 2007 on labor market outcomes throughout the United States. Recent federal policy programs have allocated $18 billion towards subsidizing the spread of this technology, especially to rural areas. Understanding the interplay between technology, firms, and the labor market is important for evaluating whether additional scarce government resources should be allocated to improve this type of infrastructure. Using models that include county and time fixed effects, I find that gaining access to broadband services in a county is associated with about 1.8 percentage points increase in employment rate, with larger effects in rural and isolated areas. Most of the employment gains result from existing firms increasing the scale of their labor demand and from growth in the labor force. These results are consistent with a theoretical model in which broadband technology is complementary to skilled workers. I find larger effects among college-educated workers, and in industries and occupations that employ more college-educated workers. Second, I analyze the adoption and use of information communication technologies (ICTs) by firms and their effects on employment and wages. I use a confidential data set from Turkey that includes detailed surveys focused on how ICTs and the Internet are used by firms. By using the rich survey data, I create an ICT index summarizing ICT adoption and use, along with the skills of the firms, where each category takes into account many applications. The firms with different levels of ICTs differ in many characteristics. I use the generalized propensity score matching method in order to compare firms that are similar in many dimensions such as industry, location, investments, profits, trade balance, and output. I find positive effects of ICTs on employment and wages that are diminishing after a certain level of ICT. These significant effects are due to an increase in ICT-generated jobs and not due to an increase in non-ICT jobs in the short-run. The effects on non-ICT employment become significant a couple years after investments in ICTs. This implies a change in the skill composition of the firms with higher intensity of ICT use, especially in the short run. Third, I analyze workers' ICT skills, and their effects on employment opportunities in developing countries. I employ a confidential data set provided by

theTurkish Statistical Institute that includes detailed surveys on ICT use by households and individuals. The data contain information on ICT skills; from the most basic ones to more advanced skills. Workers who have ICT skills are more likely to be employed when individual and household-level observables are held constant. However, this positive relationship is due to the workers who gain these skills at work. These data suggest that for this sample there is significant on-the-job learning for ICT skills, and off-the-job ICT skill acquisition does not lead to higher chances of being employed.

Anneme ve Babama

To Mom and Dad

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Chapter 1

General Introduction

This dissertation analyzes the adoption and use patterns of the Internet and information communication technologies (ICTs), and how they affect labor market outcomes. The focus is on the United States and the emerging market of Turkey. Evaluating the impact of ICTs on the economy has important policy implications. For example, recent policy programs in the United States have allocated over $17 billion towards subsidizing the spread of broadband technology, especially to rural areas. These technologies are less common in emerging countries such as Turkey and there are recent policies that aim to improve broadband access to achieve higher rates of development. Understanding the interplay between technology, firms, and the labor market is important for evaluating whether additional scarce government resources should be allocated towards improving broadband infrastructure.

In the second chapter, *The Effects of Broadband Internet Expansion on Labor Market Outcomes*, I use data from the Federal Communications Commission on broadband availability across U.S. zip codes from 1999 to 2007, matched to county-level data on employment, average earnings, and other labor market outcomes. By comparing changes in labor market outcomes in areas that gained broadband access to changes in areas without access, I isolate the effect of broadband technology while controlling for time-invariant characteristics of local labor markets. The results indicate that gaining broadband access is associated with a 1.8 percentage point increase in the employment rate. The employment effects are particularly large in counties with a larger fraction of college-educated workers and within industries that employ college-educated workers. However, my estimates of the employment effect of broadband are less than other estimates in the literature because other studies conflate the effects of broadband access in an area with other, perhaps unobserved, factors that also influence economic outcomes.[1]

I find that the decrease in unemployment rate is less than the increase in ratio of population employed. The increase in population and the increase in labor force explain around 60 percent of the increase in employment due to broadband expansion. The decrease in unemployment explains around 10 percent of

[1] Crandall, Lehr and Litan (2007), Lehr, Osorio, Gillett and Sirbu (2005). Kolko (2010) makes the first attempt to solve the endogeneity problem. He uses the slope of the terrain as an instrument for broadband deployment. He finds that this instrument is sensitive to specifications and does not lead to a conclusive result.

the increase in employment. These results suggest that the increase in employment is not solely due to unemployed workers finding jobs but also migration of the labor force.

I address the endogeneity problem using county fixed effects models, timing of the panel data and falsification test. I find evidence against reverse causality as the past levels of broadband predict current employment levels and not vice versa.

One of the contributions of this study is analyzing broadband as a skill-biased technology. There is well-established literature on skill-biased technological change. ICTs are conventionally placed in this category because they require certain skills to be employed.[2] The empirical patterns I uncover are consistent with a theoretical model of the economy in which firms combine skilled and unskilled workers, and broadband technology represents a technological improvement that increases firms' demand for skilled workers.[3] These results indicate that the recent subsidies to expand broadband may, in fact, achieve some of the goals of improving economic outcomes, but will likely also further the divide between lower and better-educated workers more generally.

Other chapters analyze the impacts of ICT use on labor market outcomes and firm performance in the emerging market of Turkey. Turkey is an interesting case to study because its broadband penetration is lower than in the United States (the penetration rate is over 90 percent in the United States and about 30 percent in Turkey) and because unique data is available in that country. Since Turkey is at an earlier stage of ICT diffusion, the economic consequences of this technology may be more pronounced. At the same time, the opportunity cost of government spending is higher in poorer, emerging countries.

ICT use impacts labor market outcomes, such as earnings and employment, through its effects on both firms and individuals. My goal is to separate these two effects by using a unique data source. The Turkish data sets contain individual and firm-level responses to questions about ICT use, therefore they allow me to go beyond the aggregate county-level analysis I have done for the United States. These projects involve restricted-use data from Turkey, provided by the Turkish Statistical Institute and State Planning Organization. Detailed surveys are conducted from 2005-2010 on how much and for what purposes ICTs and the internet are used by individuals and firms. These data sets can only be accessed at the Turkish Statistical Institutes data research center computers in Ankara, Turkey since they include confidential information about firms and individuals.

The third chapter, *ICT Use and Labor: Firm Level evidence from Turkey*, estimates the impact of ICT adoption and use on employment and wages within firms. I use two variables to measure the ICT intensity at the firm level: an ICT index and advanced internet use indicator. First, I create an ICT index summarizing

[2] Autor (2001), Autor *et al.* (2003), Acemoglu (1998) and Michaels *et al.* (2010)

[3] Adopted from Krusell *et al.* (2000)

many highly correlated indicators. The results are robust to using different weighting methods. Second, the advanced internet use variable shows whether the firms use three or more ICT use indicators chosen based on the literature: enterprise resource planning, supply chain management, customer relationship management, education, purchasing, customer support and extranet.[4] These applications are known to lead to organizational change.

The ICT Index and advanced internet use variables are positively correlated with total employment levels in the firm fixed effects models that remove the unobserved heterogeneity at the firm level. The positive correlation between ICTs and employment is due to the relationship between ICTs and ICT-related employment (ICT experts and ICT users). There is no significant relationship between ICTs and non-ICT employment. These results suggest that ICTs have direct effects on ICT-related employment: firms that adopt and use these technologies hire workers in order to maintain and use the new technologies. The scale effects that increase the demand for other types of employment is not significant for the two year fixed effects models. However, these effects might require longer periods of time to emerge, and this panel might not be long enough for them to be significantly present. Additionally, the four-year firm fixed effects regressions that do not include full controls have significant positive coefficients on non-ICT employment. Overall, the evidence indicates that, in the short term, ICT investment leads to increases only in ICT-related workers. Over a longer period, there are more significant and increasing effects on non-ICT employment through scale and productivity effects.

There is an endogeneity problem in analyzing the relationship between ICTs and employment due to reverse causality and self-selection. I address this problem in two ways. First, I use the generalized propensity score matching that removes these observable biases.[5] This method calculates the effect of ICTs on employment and wages by only comparing firms that are similar in many dimensions such as industry, location, ownership status, exports, imports and value-added. I find positive effects of the ICT index on employment and wages within firms, and these effects diminish after a certain level of ICT investment. When the ICT index increases from 0 to 0.8, employment increases by 5 percent, and wages increase by 8 percent within the firms; these effects stay constant for ICT index levels 0.8 to 1. Second, I use regional broadband deployment rates and firm's opportunity to outsource ICT tasks as instrumental variables for advanced internet use to obtain further evidence on causality. I find different sets of instruments to be valid for different industries and different technology use classifications within the same sector. Falsification tests confirm the previous results.

[4] Forman, Goldfarb and Greenstein (2011) use these Internet applications to create and advanced internet use measure. These applications are selected based on their effect on the organizational change.

[5] Generalized propensity score is developed by Imbens&Hirano (2004) and Imai&Van Dyke (2004) and it extends the propensity score for binary treatments to continuous treatment variables.

The fourth chapter, *ICT skills and Employment Opportunities* is an individual-level analysis of how ICT skills and internet job search affect workers' job market outcomes. The worker-firm matching process is highly affected by the flow and quality of information [Autor (2000)]. The ICTs, especially the Internet, provide new mechanisms to improve the matching of workers with firms. My research questions in this project are how ICT use and skills affect employment opportunities of workers. Skill levels are conventionally measured by education, however innovative capacity and knowledge are not necessarily captured by the educational attainment. In order to establish the relationship between technology use and labor market outcomes, observing the technology related skills and knowledge of workers is important. This project aims to provide new evidence on the relationship between the ICT skill levels and labor market outcomes of workers.

The data contains information on ICT skills starting from the most basic, such as using an excel spreadsheet and uploading or transferring files to more advanced skills such as knowing a programming language and solving computer problems. There is also information on how people gained these skills such as at an educational institution, at work, and through friends and family. Data indicates that most of the workers who look for jobs online also have higher ICT skills. When controlled for ICT skill levels, the positive correlations between internet job search and employment disappear. On the other hand, workers that have more advanced ICT skills are more likely to be employed when individual and household level observables are held constant. However, this positive relationship is due to the workers who gain these skills at work. These data suggest that for this sample there is significant on-the-job learning for ICT skills, and off-the-job ICT skill acquisition does not lead to higher chances of being employed.

Chapter 2

The Effects of Broadband Expansion on Labor Market Outcomes

2.1 Introduction

Broadband is an advanced telecommunication technology that allows data to be transmitted at increasingly faster speeds and is crucial for the Internet to realize its true potential. This technology is primarily deployed by private-sector firms, and diffusion proceeds from places where the technology is most profitable, such as urban areas, to other areas. The digital divide between areas that have broadband and those that do not is a serious policy concern because of the common belief that lack of access to a high-speed Internet connection has adverse economic and social costs in unserved areas. This paper uses the major expansion in broadband access between 1999 and 2007, when coverage went from 60 percent of the population to 96 percent, to evaluate the effect of broadband deployment on labor market outcomes.

Expanding broadband access to all areas of the United States remains an important policy goal. The broadband stimulus package passed in 2010 as a part of the American Recovery and Reinvestment Act that provides $7.2 billion for broadband deployment and data mapping. President Obama's 2012 fiscal budget devoted another $10.7 billion to expand broadband access. The first stated goal of these policies is to increase economic growth, employment, and productivity. The second goal is to close the digital divide by subsidizing deployment of broadband in unserved and underserved areas. Despite the enormous amount of money allocated to expanding broadband infrastructure, there is little convincing evidence about the causal effect of this technology on labor market outcomes. Locations with higher levels of population density, employment, and income have higher broadband deployment. But the diffusion of broadband is not random because private firms build the infrastructure in places where it is most profitable.[1] Thus, ordinary least squares (OLS) models of the relationship between broadband and labor market outcomes are likely to be biased towards finding a positive relationship even in the absence of a causal effect. This endogeneity has not been convincingly addressed in the recent literature on the impact of broadband on the labor market.[2]

[1] Some of the previous studies on the diffusion and determinants of broadband access are Greenstein and Prince (2008), Chaudhuri and Flamm (2007), and Prieger (2002).

[2] Kolko (2010) uses slope of the terrain as an instrument for broadband deployment but finds implausibly large estimates. He finds that this instrument is sensitive to specifications and does not lead to a conclusive result. Also see Gillett *et al.* (2005)

To estimate the causal effect of broadband access on labor market outcomes, I exploit the timing of changes in broadband access within counties over time and relate these to changes in labor market outcomes in the same county. Estimates with county and year fixed effects indicate that going from no broadband availability to ubiquitous availability within a county increases the percentage of population employed by 1.8 percentage points. Around 30 percent of the increase in employment is explained by an increase in the working-age population, around 40 percent by an increase in the labor force that is not due to population change, and around 10 percent by transition from unemployment to employment. These results suggest that the increase in county employment is not solely due to unemployed workers finding jobs but mostly from new workers entering the labor force. I also investigate the impact of broadband deployment on the number and size of firms in a county and find that most of the employment increases are driven by an increase in the scale of existing firms, rather than an increase in the number of firms in a county. These estimates of the employment effect of broadband are smaller than other estimates in the literature because other studies conflate the effects of broadband access in an area with other, perhaps unobserved factors that also influence economic outcomes.

In addition to measuring the effects of broadband deployment on labor market outcomes, I investigate how these effects vary based on location characteristics. One essential goal of the broadband stimulus program is to close the digital divide by deploying infrastructure to unserved and underserved areas, which are typically rural areas. Thus, the differential effect of broadband on rural and urban locations will have important policy implications. Broadband technology is expected to benefit isolated markets though opening up new business and employment opportunities. The broadband coefficient on most rural locations is 2.2 percentage points, which exceeds the impact in more urban locations. Rural and isolated locations benefit most from broadband as they integrate with the rest of the national market for goods and labor.

The empirical patterns I uncover are consistent with a theoretical model of the economy in which firms combine skilled and unskilled workers, and broadband technology represents a technological improvement. This skill-biased technical change model, with broadband-skilled labor complementarities, suggests that demand and wages for skilled labor increase with broadband expansion. I find that the employment effects of broadband are particularly large in counties with a larger fraction of college-educated workers and within industries that employ college-educated workers. These results indicate that the recent subsidies to expand broadband may, in fact, achieve some of the goals of improving economic outcomes, but will likely also further the divide between lower and better-educated workers more generally.

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and Crandall *et al.* (2007).

2.2 Broadband and the Labor Market

Broadband access can affect supply and demand in the labor market through several mechanisms. On the supply side, Internet job search methods can increase workers' job opportunities. Because broadband allows information about jobs to flow more quickly to a wider audience, it can improve the worker-firm matching process.[3]

On the demand side of the labor market, broadband directly boosts employment since labor is required for deployment, maintenance, and manufacturing of the infrastructure and consumer parts. Second, broadband may affect employment through the demand for the firm's products. Through e-commerce demand for goods and services can move beyond local demand. Businesses can target larger geographical markets and more customers. E-commerce can also negatively affect businesses that are most dependent on local market demand. The competition from big online stores can hurt local retail stores. In addition, broadband provides access to home entertainment options such as downloading or streaming movies and playing interactive video games that can decrease the demand for local entertainment options.

Third, broadband can affect the way the firms operate. The literature on skill-biased technological change is well-established. Information communication technologies (ICTs) are conventionally placed in this category because people must have certain skills to be employed in this field.[4] ICTs can be complementary to skilled labor for various reasons. First, these technologies are maintained and used mostly by skilled labor. Second, skilled labor might be better equipped to adapt to technological innovation. ICTs can further increase the productivity of skilled labor through increased access to resources and information. Third, computers and databases can replace some routine labor tasks, and this substitution may have larger effects on employment when there is more broadband access. As an ICT, broadband may complement some high skilled tasks and substitute some low skill tasks.

My research focuses on testable implications of this third channel through which broadband may affect employment and the labor market. I present a model with ICT-skill complementarity.[5] Firms use a technology that exhibits constant returns to scale to capital (k_t), unskilled labor (u_t), skilled labor (s_t), and information communication technology (ICT_t)

$$y = g(k_t, u_t, s_t, ICT_t) \tag{2.1}$$

The production function is Cobb-Douglas over capital and constant elasticity of substitution function of

[3] Autor (2001) discusses possible effects of Internet on how workers and firms search for one another and how labor services are delivered.

[4] Autor (2001), Autor *et al.* (2003), Autor *et al.* (1998), Acemoglu (1998, 2002), and Michaels *et al.* (2010).

[5] Adapted from Krusell *et al.* (2000).

u_t, s_t and ICT_t,

$$g(k_t, u_t, s_t, ICT_t) = k_t^{\alpha}[\mu u_t^{\sigma} + (1-\mu)(\lambda ICT_t^{\rho} + (1-\lambda)s_t^{\rho})^{\sigma/\rho}]^{(1-\alpha)/\sigma}, \tag{2.2}$$

where μ and λ are the income shares, σ and ρ are the elasticity of substitution between unskilled labor, ICT, and skilled labor. (σ and $\rho < 1$). The elasticity of substitution between ICT (or skilled labor) and unskilled labor is $1/(1-\sigma)$, and the elasticity of substitution between ICT and skilled labor is $1/(1-\rho)$. ICT-skill complementarity requires $\sigma{>}\rho$, as estimated by Krusell *et al.* (2000) and supported by other micro evidence.

Firms are price takers, and factor prices are equal to marginal products per unit of work. Then, the marginal rate of technical substitution between the labor inputs can be expressed as a function of input ratios:

$$ln(\frac{w_s}{w_u}) \simeq \lambda\frac{\sigma-\rho}{\rho}ln(\frac{ICT}{s})^{\rho} + (1-\sigma)ln(\frac{u}{s}) \tag{2.3}$$

If $\sigma{>}\rho$, this means the elasticity of substitution between ICT and skilled labor is below the elasticity of substitution between ICT and unskilled labor. This implies that ICT and skilled labor are complements. Thus, the relative demand and wages for skilled labor will go with an increase in ICT investment. As the difference between σ and ρ increases, as there are more complementarities between ICT and skilled labor compared to ICT and unskilled labor, the positive effect of ICT on skilled labor wages also increases.

This model predicts that as ICT level increases, relative wages and demand for skilled labor increases. Also, as the complementary relationship is higher between ICT and skilled labor, there is a higher positive impact of ICT on demand for skilled labor. If this hypothesis is true, broadband expansion will have a positive effect on wages and employment in locations, industries and occupations that have a higher share of skilled labor force.

2.3 Data

To measure the effects of broadband deployment on the labor market, I match broadband deployment data from the Federal Communications Commission (FCC) with labor market and demographic data from Census, Bureau of Labor Statistics (BLS), and County Business Patterns and American Community Survey (ACS).

I use the FCC Form 477 data to measure broadband deployment in an area. The FCC requires broadband companies to report if there is at least one subscriber in the zip code for Internet services of at least 200 kilobit per second (kbps). Form 477 provides information on the number of broadband providers from 1999 to 2007 focusing on availability, not on adoption by businesses and households. This does not necessarily cause a problem for my analysis. Using information on availability is appropriate for policy analysis since most broadband policies aim to increase deployment, with adoption being a byproduct. On the other hand, this data set has some drawbacks and limitations. First, it does not provide information on price, speed, or the technology of the broadband access. Second, the definition of high-speed Internet in the FCC data set is now outdated. The ARRA broadband stimulus package considers locations that have speeds less than 768 kbps as unserved. A location may be classifies as unserved in the ARRA policy, but served in the FCC data. Despite these issues, the FCC data set remains the only source of nationwide broadband information.

The FCC data are at the zip code level, which is not the appropriate geographic unit to study since most people reside and work in different zip codes. Therefore, I use the county as the unit to evaluate labor market outcomes. Zip codes are designed for the purpose of making the U.S. Postal Service (USPS) more efficient when delivering mail; they do not necessarily correspond to governmental units, such as counties or Census Bureau areas. To solve this problem, the Census Bureau has developed zip code tabulation areas (ZCTAs), which are area representations of the USPS zip codes.[6] I match FCC zip codes to Census ZCTAs and use that as my sample of zip codes.

For each ZCTA, I create an indicator for whether broadband is available. For each county, I create a weighted average of these indicators, with the weight equal to the ZCTA population from the 1990 Census, since more recent population measures could be affected by broadband availability. In any case, my results are not affected by the use of the population from other years. This weighted average of broadband indicators can be interpreted as the fraction of a county population that has broadband access.

I use Census data for demographic information, BLS data for information about employment, unemployment, and the labor force, County Business Patterns data for employment indicators, the wage rate, and the number of establishments for different sectors within a county, and ACS data for employment by occupation. I obtain urban influence Codes from Economic Research Service and rates of employees using computers and the Internet at work from the BLS. Matching all these data sets creates a panel of 3116 counties over nine years.

Broadband deployment has increased dramatically over the last decade. Figure 2.1 shows the expansion of broadband over the years at the zip code level. In 1999, 54.2 percent of zip codes had broadband access. This percentage increased to 87.8 percent by 2004. Since 2005, about 91 percent of zip codes have broadband

[6]The Census Bureau determines the ZCTAs as follows: The majority zip code is determined for each Census block and a ZCTA code is assigned to all the blocks that contain addresses with zip codes. ZCTA coverage is then extended to adjacent blocks not assigned to a ZCTA code. ZCTAs become the area representations of the zip codes through this process and by excluding unique zip codes that represent a single building and post office boxes that are served by other zip codes.

access. Thus, the data analyzed in this paper represent an important period when broadband expanded to cover nearly the entire United States. This period is important to analyze because the adoption patterns and people's and firms' use of this technology is still changing. Figure 2.2 shows national broadband adoption rates by households between 2000 and 2007. Broadband adoption increased from 30 percent to almost 60 percent between 2004 and 2007, even though broadband deployment levels stayed around 90 percent during those years.

Table 2.1 shows the means of demographic and labor market characteristics by quartiles of ratios population living in an area where broadband is available. The F-statistics are for difference-in-means tests among the different quartiles. All demographic characteristics are statistically significantly different for locations with different levels of broadband availability. It is clear that areas with more broadband coverage are different from areas with less: The locations with higher broadband deployment levels are urban areas that have higher population density and income. While these differences in observables can be controlled for in a regression, the differences in observables suggest that there might also be differences in unobservables or unmeasured characteristics. OLS models that omit these variables will likely overestimate the effect of broadband access on employment. Therefore, I use county fixed effects to eliminate the omitted variables bias that stems from time-invariant differences between counties. Identification comes from within-county variation over time in broadband availability levels and labor market outcomes.

2.4 Empirical Specification and Results

My empirical specification exploits the panel structure of the data: County fixed effects absorb any permanent heterogeneity at the county level. Time fixed effects absorb time-specific shocks and trends that are shared by all locations. I model the employment-to-population ratio in county c at time t as

$$\text{Employment rate}_{ct} = \beta_0 + \beta_1 \text{Broadband}_{ct} + \delta X_{ct} + \alpha_c + \lambda_t + \epsilon_{ct}. \tag{2.4}$$

$Broadband_{ct}$ is the ratio of the population living in a broadband available area in county c at time t, X_{ct} includes control variables such as population density, income, and other demographics, α_c is the county fixed effect term, and λ_t is the time fixed effect term.

Table 2.2 presents the OLS regressions and county fixed effects regressions where the dependent variable is the ratio of employed people among the working-age population (16 and older). All specifications include control variables for county characteristics. Column 1 is a basic OLS model without time controls. Based on the OLS, when a county goes from no broadband availability to ubiquitous availability, the ratio of the population employed increases by 3.3 percentage points. When time controls are included in column 2, this effect decreases to 3.2 percentage points. Column 3 adds county fixed effects and uses the within-county variation over time to eliminate the unobserved heterogeneity between locations. The broadband coefficient remains significant with the county fixed effects model but its magnitude drops by a quarter. Based on the county fixed effects model, moving from no availability to full availability increases the percentage of population employed by 2.52 percentage points. Using variation within counties instead of across counties takes out the spurious correlation between broadband and employment that is due to unobservable characteristics of the counties. This leads to a drop in the magnitude of the broadband coefficient. In column 4, time fixed effects are included, as well as county fixed effects; the broadband impact on percentage of employed working population falls to 1.8 percentage points. Controlling for time effects takes out some of the correlation between broadband and employment. I use county and time fixed effects model as my baseline because it provides the most robust estimates.[7]

The significant relationship between broadband and employment might be due to high economic growth in the area. Extra control variables are added to county and time fixed effects regressions to capture the growth and market activity in the area that might not be captured by demographic variables. These additional variables are the growth rate of county income and log of number of establishments. Table 2.3 presents the results of county and time fixed effects regressions with these extra control variables. The broadband coefficient's magnitude does not significantly change when I control for local market activity. The results are robust to these additional specifications.

Table 2.4 explores whether the increase in employment is associated with movements into the labor force or movements from unemployment to employment. The dependent variables in Columns 1 through 4 are the logarithms of the county population, the number of people in the labor force, the number of people employed in the county, and the number of unemployed people in the county, respectively. Gaining full broadband access is associated with a 0.36 percent increase in the county working-age population (16 and older) and a 2 percent increase in the labor force. Employment increases by about 2.3 percent, slightly more than the increase in the labor force (though this difference is not statistically different from zero). County unemployment decreases by about 4.6 percent. For a county that is at the median of the population, employment, and labor force distribution, the decrease in the number of unemployed people explains around 11 percent of the increase in the number of people employed. Around 30 percent of the increase in employment can be explained by an increase in the working-age population. Around 40 percent of the increase in employment is due to an increase in the labor force that cannot be attributed to increase in population.

[7]One concern about using nationwide geographical data is spatial correlation. The significance of the results are robust to allowing the error terms to be cross-sectionally dependent and autocorrelated.

More job opportunities and lower search costs may be reasons that lead these people to move into the labor force. This pattern of results indicates that the employment increases tend to come from people who previously lived in a different county and from people who were not previously in the labor force.

The increase in the number of employed workers can be accounted for by an increase in number of establishments in the county and by increased hiring by existing establishments. I use county and time fixed effects models to explore the effects of broadband access on these channels. Column 1 of Table 2.5 shows that there is a positive effect of broadband on the log of the number of establishments. Gaining broadband access is associated with about a 0.5 percent increase in the number of establishments in the county. This change explains around 22 percent of the increase in the number of employed people. In column 2, the broadband coefficient suggests that average employees per establishment increases by 1.6 percent. Changes in employees per establishment explains around 65 percent of the change in number of employed people. Broadband access seems to attract firms to an area and also expand the employment base of firms. The major effect is due to an increase in the size of firms.

2.5 Broadband as a Skill-Biased Technology

The model presented in Section 2 predicts that the expansion of broadband infrastructure will lead to an increase in the demand for skilled labor. To test this prediction, this section investigates whether employment gains are larger for counties, industries and occupations that have a higher share of college-educated workers.

First, I test whether the counties that have more skilled labor force attain larger employment and wage increases with broadband expansion. Table 2.6 presents results from fixed effects regressions that include interaction terms between broadband and the fraction of the county population with a college degree or higher in 2000. Columns 1 and 2 model the employment rates and columns 2 and 3 model the log of total payroll in the county. Column 1 repeats the basic employment model shown earlier. Column 2 includes the interaction term between broadband and the college graduation rate, which is 0.15 and statistically different from zero. Column 3 presents the county and time fixed effects model where the dependent variable is the log of payroll per employee in the county. Broadband expansion is associated with around 1 percent higher average wages in the county. The interaction term between broadband and the college graduation rate is significant and positive as well.

Table 2.7 interprets the interaction coefficients between broadband and college graduation rates. The first row of the table shows the 25^{th} percentile, 50^{th} percentile, and 75^{th} percentile of the distribution of the fraction of county population with a college degree. The second row evaluates the effect of gaining full broadband access for counties at each of these three points. A county at the 25^{th} percentile has a college graduation rate of 16.9 percent. Gaining broadband access in such a county is associated with a 1.5 percentage point increase in the employment rate. For a county at the median of the skill distribution, moving from no availability to full availability increases the percentage of employed population by 2.1 percentage points. For a county on the 75^{th} percentile of the same distribution, the effect goes up to 2.99 percentage points. The effect of broadband on wages per employee is higher in counties that have more skilled labor force. The coefficient on the log of average payroll per employee is 2.8 for a county that is at the median of skill distribution. These patterns are consistent with the theory that broadband and skilled labor are complements and that broadband increases firms' demand for skilled labor.

Next, I investigate whether there are differential effects on the number of establishments and employee per establishment based on the skill composition of the locations. Columns 2 and 4 of Table 2.8 include the interaction term between broadband and skill proxy. The significant positive effect of broadband on number of establishments and employees per establishment is higher in locations with a higher share of educated population. Table 2.9 presents the broadband effects on counties that are at the 25^{th}, 50^{th}, and 75^{th} percentiles of the skill distribution using the results from Table 2.8. For a county that is on the median of the distribution for college graduates, the broadband coefficient of the log of number of firms is 0.022 and the coefficient of the log of employees per establishment is 0.028. These results suggest that both an increase in the number of firms and an increase in firm size contribute to growth of employment for skilled labor. The broadband effects on the employees per establishment are higher than the broadband effects on the number of establishments for the entire skill distribution.

Another approach to test the skill-biased technological change hypothesis is to analyze differential effects on industries. As different industries have different skill compositions and local demand dependence, they are expected to be affected differently by broadband expansion. Table 2.10 lists the broadband coefficients for different industries from models that include county and time fixed-effects. Column 1 uses the logarithm of employment in the industry as the dependent variable. In columns 2 and 3, the dependent variable is the logarithm of employees per establishment and logarithm of payroll per employee, respectively.

To analyze how these coefficients change based on the skill levels in the industries, I plot the broadband coefficients in Table 2.10 against the different proxies for skill levels. The first proxy is the percentage of college graduates employed in the industry as of 1999. The second proxy is the percentage of the employees who use computers at work and the third proxy is the percentage of the employees who use the Internet at work. The Bureau of Labor Statistics provides these two skill measures for 2003.[8]

[8]These measures are available for 1998 and 2001 as well. Even though these proxies change over time within the industries, the ranking of the industries do not change and graphs look similar using proxy measures from other years.

Figure 2.3 plots the broadband coefficients for the logarithm of employment in Table 2.10 against the percentage of college graduate employees by industry. There is a positive relationship between the broadband coefficients and share of college graduates. Figures 2.4 and 2.5 graph the coefficients of the log of average payroll against the percentage of employees who use a computer and the percentage of employees using the Internet at work, respectively. These graphs show a similar positive relationship between broadband effects and skill levels. The largest effects of broadband expansion on employment are in sectors that have a high ratio of skilled labor such as professional and technical services, finance, and information. The coefficients for the agriculture and mining sectors are insignificant, as broadband cannot replace manual labor jobs. Broadband expansion has a negative effect on the industries in the lower end of the employee skill distribution. Sectors such as sales and services include more routine labor tasks that can be replaced by technology. Also sectors such as retail and entertainment are more dependent on local demand and could be negatively affected by online competition.

Figure 2.6 plots the broadband coefficients for the logarithm of average payroll against the percentage of employees who are college graduates by industry. The regression line indicates that, as the ratio of college graduates goes up, the broadband coefficients become more positive. Figures 2.7 and 2.8 graph the log of average payroll against the percentage of employees using computers and the percentage of employees using the Internet at work. The graphs are similar for these skill proxies as well.

Figures 2.9 and 2.10 plot the broadband coefficients of the logarithm of employees per establishment over the percentage of college graduate workers in each industry and percentage of employees using computers at work. These graphs show a similar pattern as well: more positive effects on skill-intensive sectors such as information, finance, and professional services. However, the positive relationships between coefficients and skill levels are not statistically significant. The relationship between the skill proxy and broadband coefficients become stronger but are still not to significant in Figure 2.11, where percentage of employees using the Internet at work is used to measure skill level.

Every sector has characteristics that are differently affected by broadband expansion and e-commerce, but overall there are more positive effects on the sectors that have a higher share of skilled labor. A 1 percentage point increase in the percentage of employees with a college degree or above corresponds to .013 percentage point larger broadband coefficient on the log of employment, 0.009 percentage point significantly higher broadband coefficient on log of payroll per employee, and 0.003 percentage point insignificantly higher broadband coefficient on employee per establishment within the sector. These results provide further evidence that broadband technology is complementary to skilled labor.

The final strategy I use to test the skill-biased technological change hypothesis is to analyze differential effects across occupations. The model predicts that the impact of broadband will vary based on the skill content of the occupation. To investigate this, I create a panel of 1349 counties using the 2000 Census and the 2005-2007 three-year American Community Survey data. I estimate models of the log of employment on broadband deployment separately by occupation, including county and time fixed effects and demographic control variables. In Figure 2.12 I plot the broadband coefficients from these models on different occupations against the percentage of employees using the Internet at work in different occupations. There is a significant positive relationship between the skill level of the occupation and corresponding broadband coefficient. Figure 2.13 shows a similar relationship, where the skill proxy is the percentage of employees using computers at work.

In sum, the broadband coefficients are higher in counties that have a larger skilled labor force, and in industries and occupations that disproportionately hire more-skilled labor. These findings support the skill-biased technological change hypothesis.

2.6 Broadband Effects on Rural versus Urban Locations

The locations that are left behind in broadband deployment are typically rural areas. Determining the effects of broadband on rural locations is an important concern for broadband policy since closing the digital divide is a major policy goal. Current policies advocate deployment to unserved and underserved areas as essential for creating business and employment opportunities. Broadband can help isolated markets by integrating them with the rest of the national economy. Broadband access can also help businesses, suppliers, and customers reach out to different areas. Expanding the geographical market can lead to higher production and lower costs, as well as new business opportunities. Interviews with farmers in rural areas who have received broadband access through the stimulus package indicate that their sales are higher because they use the Internet to advertise their products to anyone in the country, not just local customers.[9] Having a website and uploading pictures and videos (which is far more difficult with a dial-up Internet connection) enable firms in isolated locations to target more customers. Due to the higher production rates, the number of employees at these farms has also increased.

To investigate whether broadband has heterogeneous effects on urban and rural locations, I use the Urban Influence Codes (UIC) created by the Economic Research Service, U.S. Department of Agriculture. The urban influence codes form a classification scheme that distinguishes metropolitan counties by size and non-metropolitan counties by the size of the largest city or town and proximity to metropolitan and micropolitan counties. The large metropolitan counties have at least 1 million residents, whereas the small

[9] *New York Times*, "High Speed for Sparsely Wired", July 9, 2010.

metropolitan counties have fewer than 1 million residents. Micropolitan counties are defined as urban areas based around a core city or town with a population of 10,000 to 49,999. I divide the counties into five groups using an aggregated version of UIC:

- Group 1: Metropolitan county
- Group 2: Adjacent to a large metropolitan county
- Group 3: Adjacent to a small metropolitan county
- Group 4: Micropolitan or adjacent to a micropolitan county
- Group 5: Not adjacent to a metro/micropolitan county

The first group consists of 1072 large and small metropolitan counties and constitutes most urban locations. The second and third groups are the counties adjacent to a large metropolitan county and small metropolitan county, respectively. There are 214 counties in the second group and 841 counties in the third group. The fourth group consists of 679 counties that are micropolitan or adjacent to a micropolitan county. The last group consists of 310 of counties that are not adjacent to any metropolitan or micropolitan county. This group represents the most isolated markets in the United States.

Table 2.11 presents the OLS and county fixed effects regressions including the broadband and urban influence code interactions. Group 5, the most rural and isolated locations, is the omitted category. In column 2, the broadband interaction terms with the urban influence codes compare the effect of broadband in that category to the most rural and isolated category. The broadband interaction terms are negative and statistically different from zero for all other categories. This suggests that broadband raises employment more in rural locations compared to relatively more urban and urban-influenced locations. In the most isolated locations, the effect of moving from no availability to full availability to the residents is a 2.24 percentage points increase in the employment rate. In metropolitan areas, employment increases by 1.52 percent (i.e., $2.24-0.72$). These findings are consistent with the notion that expanding broadband access provides slightly larger benefits to rural and more isolated areas.

Combining the differential effects of broadband on rural versus urban locations and on different skill levels, I employ three-way interactions between broadband, UIC, and skill level. Column 4 of Table 2.11 reports that positive effects of broadband on skilled labor are highest in the most rural counties and lowest in the most urban counties, which is consistent with the previous results. The skilled labor force in the most rural areas experiences the greatest benefits from broadband expansion.

2.7 Further Evidence on the Causal Direction

The county and time fixed effects models eliminate the endogeneity due to observable characteristics. Endogeneity due to reverse causality remains a potential problem in analyzing the relationship between broadband technology and the employment rate. Locations with higher employment levels might attract broadband providers. Obtaining a conclusive result about this problem without an instrumental variable or a natural experiment is challenging. Despite the unavailability of these opportunities, I find some evidence on the causal direction by exploiting the timing of changes in broadband access and changes in employment. I use regressions that include leads and lags of broadband and the employment rate to get this evidence. The results indicate that the causal direction is from broadband deployment to the employment rate and not vice versa.

Table 2.12 reports county and time fixed effects regressions where the dependent variable is the employment rate and the independent variables are leads and lags of broadband and the employment rate. To decide how many lags of dependent and independent variables should be present in these regressions, I first use individual t-statistics of lagged values of dependent variable. Column 1 includes broadband as an independent variable as well as two lags of the employment rate variable that are significant according to individual t-tests. Once I find the set of significant lagged values of the dependent variable, I augment the regression is by lagged values of the independent variable. Column 2 includes two lags of broadband variables and column 3 includes the lead of the broadband variable. In both of these columns, the lags of broadband variable are significant, supporting the lack of reverse causality. The lead of the broadband is not significant which further supports the causation finding. Column 4 removes the lags of broadband variables to check the robustness of the lead broadband coefficient.

Table 2.13 is similar to Table 2.12, but in this case the dependent variable is broadband rather than the employment rate. Broadband is regressed on leads and lags of both variables using a county and time fixed effects model. The lags of the employment rate are insignificant in columns 2 and 3. The lead of employment is insignificant in column 3, but it becomes significant once the lags of broadband variables are removed. This is further evidence that employment is not causing broadband expansion. The results are similar for analyses of the number of establishments and employees per establishment variables.

I next assess if the broadband effects that I estimated earlier reflect whether broadband is actually deployed, or whether the area simply has enough economic activity to attract providers using a falsification test. To do this, I analyze the relationship between employment and the existence of cable and phone companies in a county. There are two major types of broadband connections: cable connection provided by cable TV companies and ADSL connection provided by phone companies. These two types of broadband access constitute over 90 percent of all broadband connections during the time period used in this study.[10] Thus, the broadband deployment rate is highly correlated with the number of cable providers and phone companies in the area. This analysis lets me assess whether the broadband effects that I estimated earlier reflect whether broadband is actually deployed, or whether the area simply has enough economic activity to attract a cable or DSL provider.

First, I calculate the percentage of population living in an area where there is at least one competitive phone service provider. There are two types of phone companies: incumbent local exchange carriers (ILECs) and competitive local exchange carriers (CLECs). ILECs are the incumbent phone service providers which are available in every area. CLECs are the competitive phone companies that entered the market with an existing ILEC. I use the percentage of population living in an area that has a CLEC as a measure for phone service intensity. Second, I use the number of cable TV companies in the county to measure the density of cable TV provision.

Table 2.14 shows results from models of employment as a function of the percentage of population living in an area where there is a competitive local exchange provider (in column 1) and number of cable companies (in column 2). These models also include county and year fixed effects. Both coefficients are small and not statistically different from zero. I interpret this as evidence that the broadband effects presented in this paper result from actually having broadband in an area and are not driven by unobserved factors that lead a cable or phone company to enter the market.

2.8 Conclusion

The effects of broadband on the labor market have become an important policy issue, especially in light of the large broadband stimulus package. I use FCC data to analyze how broadband deployment affects the labor market outcomes across counties. Even though this data has many limitations, it is the only source for measurements of nationwide broadband deployment. I exploit the panel structure of the data set to eliminate permanent heterogeneity at the county level. I find significant effect sof broadband expansion on the employment rate using a county and time fixed effects model: moving from no availability to full availability increases the percentage of population employed by 1.8 percentage points. The employment effect is larger in rural and more isolated areas.

I interpret this effect through the lens of a model of firms' demand for skilled and unskilled labor. Broadband technology is a complement to skilled labor, and its expansion increases the relative demand for skilled labor. I find three types of evidence to support this model: first, the employment and payroll

[10] National Telecommunications and Information Administration

effects are larger in counties where a larger share of the population has a college degree. Second, I find larger increases in employment in industries that employ more college graduates. I also find payroll increases in these industries. Third, employment effects are larger in occupations that require more skilled labor. The results of this paper therefore indicate that while broadband has benefits for all segments of society, these benefits are not shared equally. In particular, broadband expansion is likely to increase the gap in labor market success between skilled and unskilled workers.

2.9 Tables and Figures

Table 2.1: Mean Demographics by Broadband Availability Quartiles in 2000

A. Demographic Characteristics

	1^{st} quartile	2^{nd} quartile	3^{rd} quartile	4^{th} quartile	F-stat (difference in means)
Median Income	29400	31287	32948	38315	414.99
Total Population	5925	14890	27305	150171	132.15
Urban Population	0.1497	0.3559	0.5090	0.5813	876.95
Population Density	0.0210	0.0442	0.1092	0.594	48.51
White	0.8528	0.8514	0.8556	0.8178	5.77
Black	0.0687	0.0901	0.0756	0.1127	15.90
Asian	0.0037	0.0054	0.0085	0.0160	79.85
Male	0.4987	0.4967	0.4948	0.4920	51.16
Age 7-15	0.1382	0.1338	0.1330	0.1322	78.31
Age 16-24	0.1098	0.1216	0.1255	0.1213	60.79
Age 25-39	0.1813	0.1926	0.2014	0.2117	358.85
Age 40-59	0.2676	0.2663	0.2653	0.2690	3.91
Age 60 or more	0.2159	0.1970	0.1829	0.1737	214.40
12th Grade or Less	0.2282	0.2235	0.2075	0.1981	54.60
High School Diploma	0.3701	0.3629	0.3408	0.3156	170.29
College Degree	0.1569	0.1637	0.1846	0.2089	181.42
Graduate Degree	0.0307	0.0374	0.0473	0.0580	307.32
Broadband Access	0.1849	0.6960	0.8864	0.9363	217.41

B. Labor Market Characteristics

	1^{st} quartile	2^{nd} quartile	3^{rd} quartile	4^{th} quartile	F-stat (difference in means)
Ratio of employed pop	0.4570	0.4625	0.4656	0.4814	62.74
Unemp Rate	4.6186	4.5232	4.3972	3.9091	59.03
Annual payroll	20620	22650	24192	26969	129.32
Establishments	293.5	760.3	2218.7	5638.5	206.34
Employee per estab	9.369	11.855	13.030	14.141	98.78

F statistics is for difference in means test across the quartiles
F critical value for α=0.01 is 3.78

Table 2.2: OLS and County Fixed Effects

Dependent Variable: Ratio of Employed Population

	(1)	(2)	(3)	(4)
Broadband	0.0337***	0.0320***	0.0252**	0.0181***
	(0.0020)	(0.0023)	(0.0008)	(0.0010)
County FE	No	No	Yes	Yes
Year FE	No	Yes	No	Yes
Observations	28044	28044	28044	28044
Number of counties	3116	3116	3116	3116

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Control variables included: income, age, race, gender, population density

Table 2.3: Fixed Effects with Market Activity Controls

	(1)	(2)	(3)	(4)
Broadband	0.0181***	0.0182***	0.0191***	0.0181***
	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Income growth rate		0.0270***		0.0270***
		(0.0022)		(0.0022)
Log of Number of Establishments			0.0168***	0.0070***
			(0.0024)	(0.0020)
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	28044	24928	28044	24928
Number of counties	3116	3116	3116	3116

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Control variables included: income, age, race, gender, population density

Table 2.4: Fixed Effects for Population, Labor Force, Employment, and Unemployment

	(1) Log of population (working age)	(2) Log of number of people in labor force	(3) Log of number of people employed	(4) Log of number of people unemployed
Broadband	0.0036**	0.0204***	0.0234***	-0.0476***
	(0.0021)	(0.0021)	(0.0022)	(0.0021)
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	28044	28044	28044	28044
Number of counties	3116	3116	3116	3116

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Control variables included: income, income growth rate, age, race, gender, population density

Table 2.5: Effects on Number of Establishments and Employees per Establishment

	(1) Log Number of Establishments	(2) Log Employees per Establishment
Broadband	0.0048**	0.0161***
	(0.0023)	(0.0030)
County FE	Yes	Yes
Year FE	Yes	Yes
Observations	28044	28044
Number of counties	3116	3116

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Control variables included: income, income growth rate, age, race, gender, population density

Table 2.6: Broadband and Skill Interaction

	(1) Employment Rate	(2) Employment Rate	(3) Log Payroll	(4) Log Payroll
Broadband	0.0182***	-0.0099***	0.0101**	-0.1285***
	(0.0010)	(0.0028)	(0.0052)	(0.0145)
BB x Fraction of county population with a college degree or higher		0.1519***		0.7615***
		(0.0143)		(0.0738)
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	28044	28044	28044	28044
Number of counties	3116	3116	3116	3116

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Control variables included: income, income growth rate, age, race, gender, population density

Table 2.7: Broadband Coefficients by Percentile of Fraction of County Population with a College Degree or Higher

	25^{th}Percentile	50^{th} Percentile	75^{th}Percentile
Fraction of county population with college degree or higher	0.1690	0.2051	0.2620
Broadband coefficient on employment rate	0.0157	0.0212	0.0299
Broadband coefficient on log of wages per employee	0.0001	0.0280	0.0710

Table 2.8: Effects on Number of Establishments and Employees per Establishment

	(1) Log Number of Establishments	(2) Log Number of Establishments	(3) Log Employee per Establishment	(4) Log Employee per Establishment
Broadband	0.0048**	-0.0899***	0.0161***	-0.0922***
	(0.0023)	(0.0063)	(0.0030)	(0.0140)
BB x Fraction of population with a college degree or higher		0.5432***		0.5882***
		(0.0315)		(0.0708)
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	28044	28044	28044	28044
Number of counties	3116	3116	3116	3116

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Control variables included: income, income growth rate, age, race, gender, population density

Table 2.9: Broadband Coefficients by Percentile of Fraction of County Population with a College Degree or Higher

	25^{th}Percentile	50^{th} Percentile	75^{th}Percentile
Fraction of county population with college degree or higher	0.169	0.205	0.262
Broadband coefficient of log of number of firms	0.002	0.022	0.052
Broadband coefficient of log of employees per establishment	0.007	0.028	0.061

Table 2.10: Industry Effects

Industry	(1) Log Employment	(2) Log Employees per Establishment	(3) Log Payroll per Employee
Agriculture	0.0504	-0.1183	0.0110
	(0.0517)	(0.1129)	(0.0490)
Entertainment	-0.0015***	0.0979	-0.0842**
	(0.0005)	(0.2249)	(0.0392)
Construction	-0.1569***	0.2160***	-0.1693***
	(0.0338)	(0.0449)	(0.0279)
Mining	0.0185	-0.0079	-0.0199
	(0.0466)	(0.0778)	(0.0405)
Other Services	-0.3390***	0.4921***	-0.2556***
	(0.0006)	(0.0418)	(0.0217)
Wholesale	-0.2823***	0.3303***	-0.2494***
	(0.0402)	(0.0548)	(0.0327)
Retail	-0.1721***	0.1225***	-0.0833***
	(0.0222)	(0.0202)	(0.0141)
Utilities	0.1487***	-0.1623**	0.0746*
	(0.0002)	(0.0718)	(0.0442)
Transportation	-0.3557***	0.2234***	-0.2334***
	(0.0505)	(0.0691)	(0.0400)
Manufacturing	0.0121	0.1984***	0.0993***
	(0.0485)	(0.0400)	(0.0301)
Educational Services	0.0194	-0.2189***	-0.0118
	(0.0479)	(0.0666)	(0.0294)
Health Care	-0.2568***	0.1112***	-0.1352***
	(0.0368)	(0.0283)	(0.0219)
Technical Services	0.4369***	0.6050***	-0.3569***
	(0.0411)	(0.0649)	(0.0348)
Management	0.0823*	-0.1109*	0.0027
	(0.0456)	(0.0639)	(0.0374)
Information	-0.0040	0.2149***	0.1412***
	(0.0506)	(0.0768)	(0.0423)
Finance	0.2239***	0.1856***	0.2050***
	(0.0373)	(0.0453)	(0.0299)
Real Estate	-0.1830***	0.2476***	-0.2166***
	(0.0480)	(0.0875)	(0.0382)
Admin Services	-0.1913***	0.3774***	-0.2456***
	(0.0569)	(0.0783)	(0.0398)
Accommodation&Food	-0.0434	0.0731	-0.0842**
	(0.0591)	(0.2249)	(0.0392)
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	28044	28044	28044
Number of counties	3116	3116	3116

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Control variables included: income, income growth rate, age, race, gender, population density

Table 2.11: Interactions Between Broadband, Urban Influence Codes, and Skill Level

Dependent Var: Ratio of Employed Population

	(1)	(2)	(3)	(4)
Broadband	0.0182***	0.0224***	-0.0099***	-0.0253***
	(0.0010)	(0.0018)	(0.0028)	(0.0070)
BB x Fraction of county population with college or higher degree			0.1519***	0.2325***
			(0.0143)	(0.0328)
Broadband x Metro County		-0.0072**		0.0644***
		(0.0030)		(0.0098)
Broadband x Adj.to Large Metro County		-0.0101**		0.0064
		(0.0044)		(0.0146)
Broadband x Adj. to Small Metro County		-0.0052**		0.0207**
		(0.0023)		(0.0086)
Broadband x Micro/Adj. to Micro County		-0.0049**		-0.0056
		(0.0023)		(0.0086)
BB x Metro County x Fraction of county population with college degree or higher				-0.1689***
				(0.0497)
BB x Adj.to Large Metro County x Fraction of county population with college degree or higher				-0.0529
				(0.0778)
BB x Adj. to Small Metro County x Fraction of county population with college degree or higher				-0.1101**
				(0.0428)
BB x Micro/Adj. to Micro County x Fraction of county population with college degree or higher				-0.0202
				(0.0416)
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	28044	28044	28044	28044
Number of counties	3116	3116	3116	3116

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Control variables included: income, income growth rate, age, race, gender, population density

Table 2.12: Lags and Leads

Dependent Variable: Employment Rate

	(1)	(2)	(3)	(4)
Lag 1 Employment Rate	0.6870***	0.6877***	0.6156***	0.6158***
	(0.0061)	(0.0061)	(0.0066)	(0.0066)
Lag 2 Employment Rate	-0.0462***	-0.0460***	-0.0462***	-0.0459***
	(0.0041)	(0.0041)	(0.0041)	(0.0041)
Broadband	0.0022**	0.0023**	0.0037***	0.0036***
	(0.00010)	(0.0011)	(0.0011)	(0.0010)
Lag 1 Broadband		0.0017**	0.0016**	
		(0.0009)	(0.0008)	
Lag 2 Broadband		0.0013**	0.0011*	
		(0.0006)	(0.0006)	
Lead 1 Broadband			-0.0012	-0.0012
			(0.0014)	(0.0014)
County FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	21812	21812	18696	18696
Number of Counties	3116	3116	3116	3116

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.13: Lags and Leads

Dependent Variable: Broadband

	(1)	(2)	(3)	(4)
Lag 1 Broadband	0.3510***	0.3499***	0.3576***	0.3277***
	(0.0069)	(0.0069)	(0.0072)	(0.0076)
Lag 2 Broadband	0.0330***	0.0323***	0.0657***	0.0186***
	(0.0054)	(0.0054)	(0.0052)	(0.0060)
Lag 3 Broadband	-0.0134***	-0.0134***	-0.0185**	-0.0111**
	(0.0040)	(0.0040)	(0.0043)	(0.0048)
Employment Rate	0.2116***	0.1034	0.2549**	0.3521***
	(0.0484)	(0.0653)	(0.0640)	(0.0805)
Lag 1 Employment Rate		-0.0648	-0.0562	
		(0.0640)	(0.0823)	
Lag 2 Employment Rate		0.0006	0.0155	
		(0.0369)	(0.0417)	
Lead 1 Employment Rate			0.0074	0.0664*
			(0.0313)	(0.0342)
County FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	18696	18696	15580	15580
Number of Counties	3116	3116	3116	3116

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.14: Cable Providers and Competitive Local Exchange Companies

Dependent Variable: Employment Rate

	(1)	(2)
Percentage of population in an area with competitive local exchange company	0.00001	
	(0.00093)	
Number of cable companies		0.00003
		(0.00006)
County FE	Yes	Yes
Year FE	Yes	Yes
Observations	28044	28044
Number of counties	3116	3116

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 2.1: Broadband Expansion by Zip codes

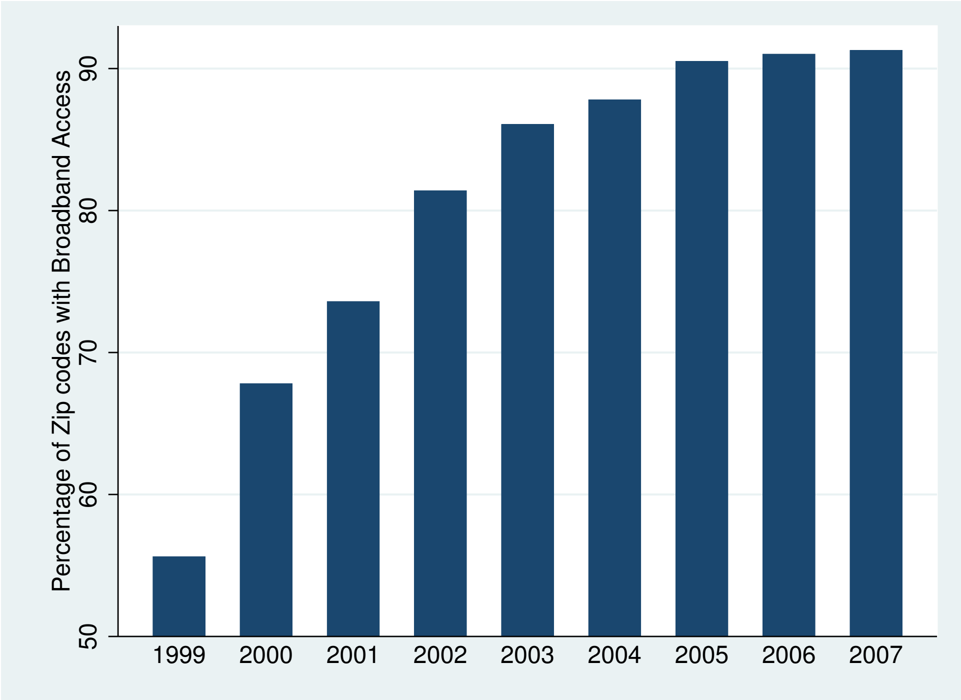
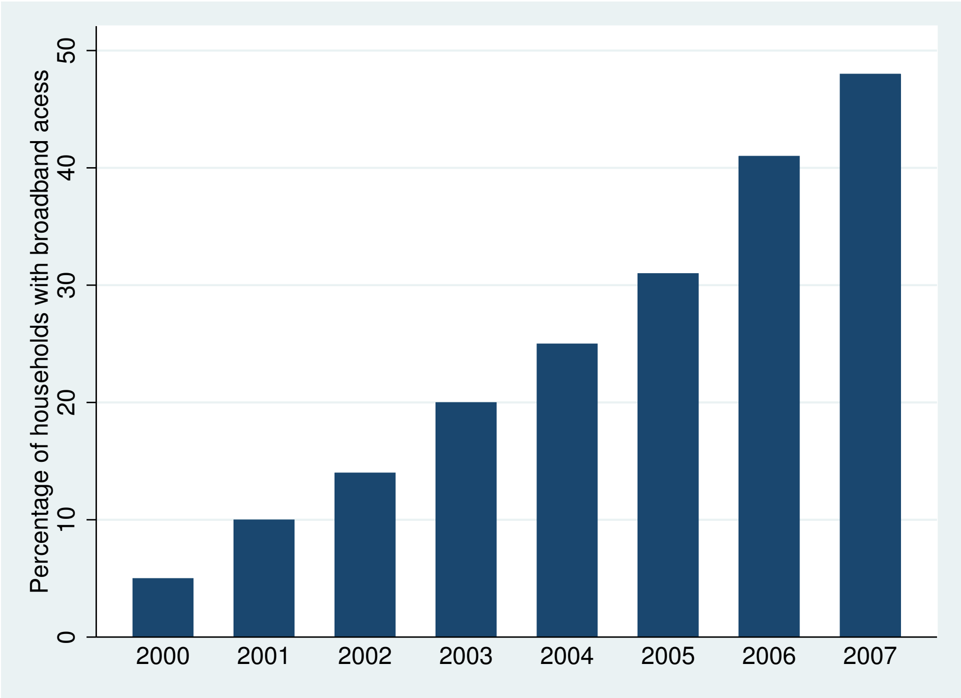


Figure 2.2: National Broadband Adoption by Households



Sources: Pew Internet & American Life Surveys, and National Telecommunication and Information Administration

Figure 2.3: Broadband Coefficients by Industry (Log of Employment)

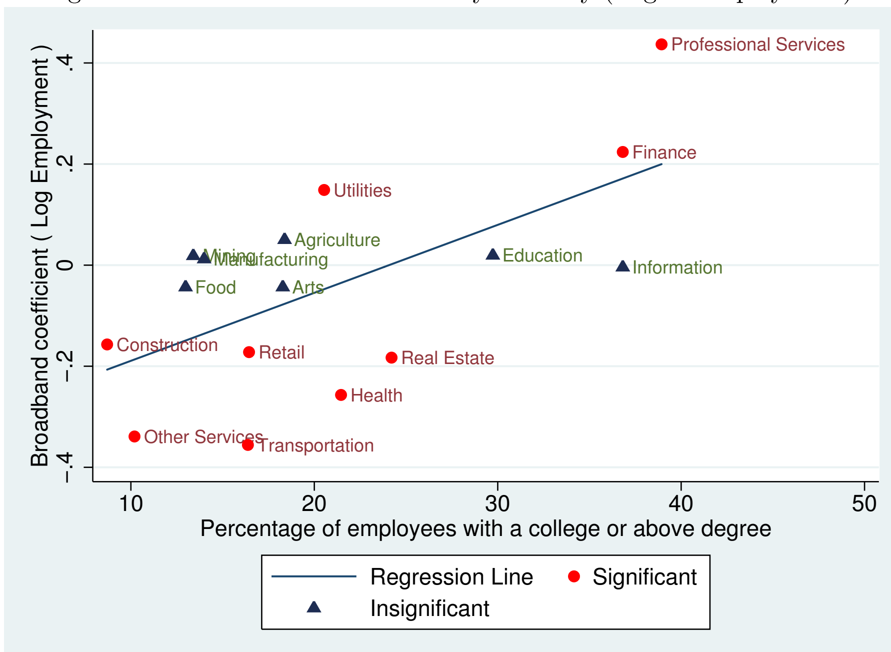


Figure 2.4: Broadband Coefficients by Industry (Log of Employment)

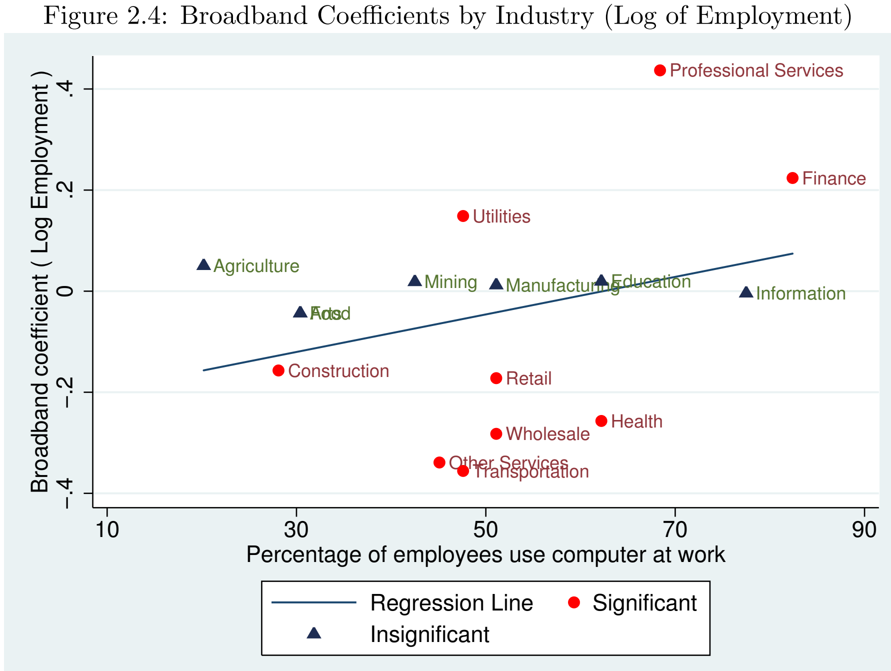


Figure 2.5: Broadband Coefficients by Industry (Log of Employment)

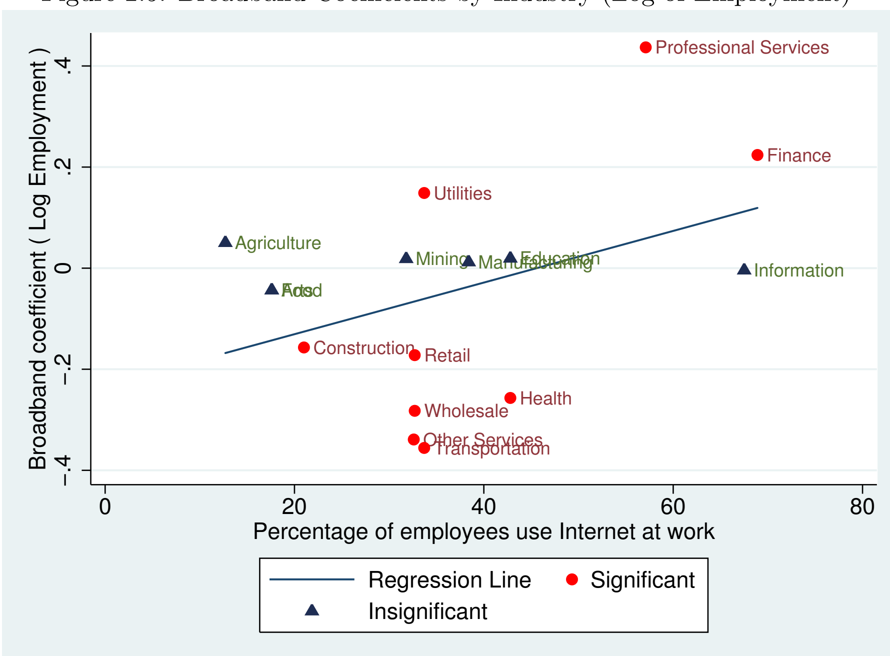


Figure 2.6: Broadband Coefficients by Industry (Log of Average Payroll)

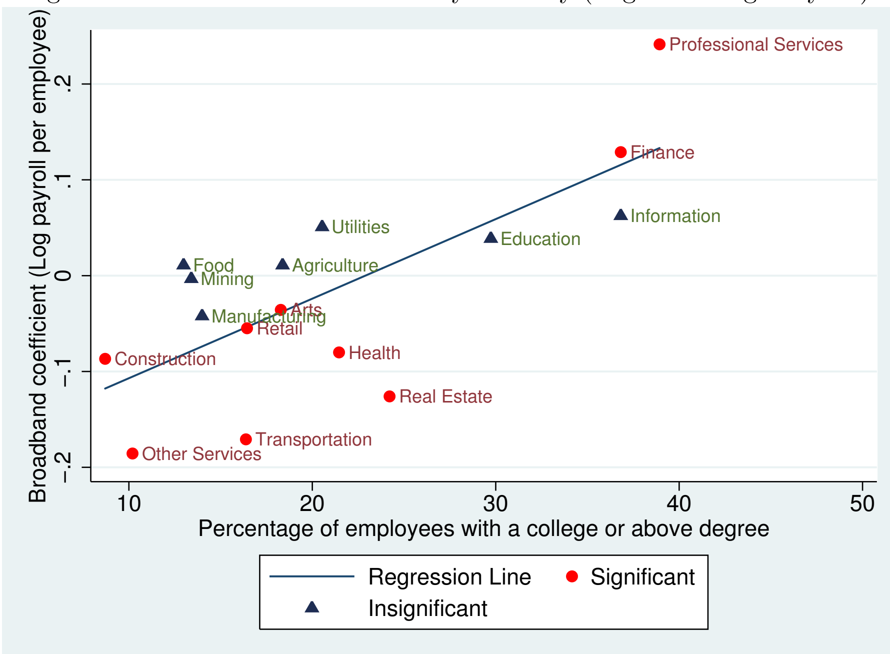


Figure 2.7: Broadband Coefficients by Industry (Log of Average Payroll)

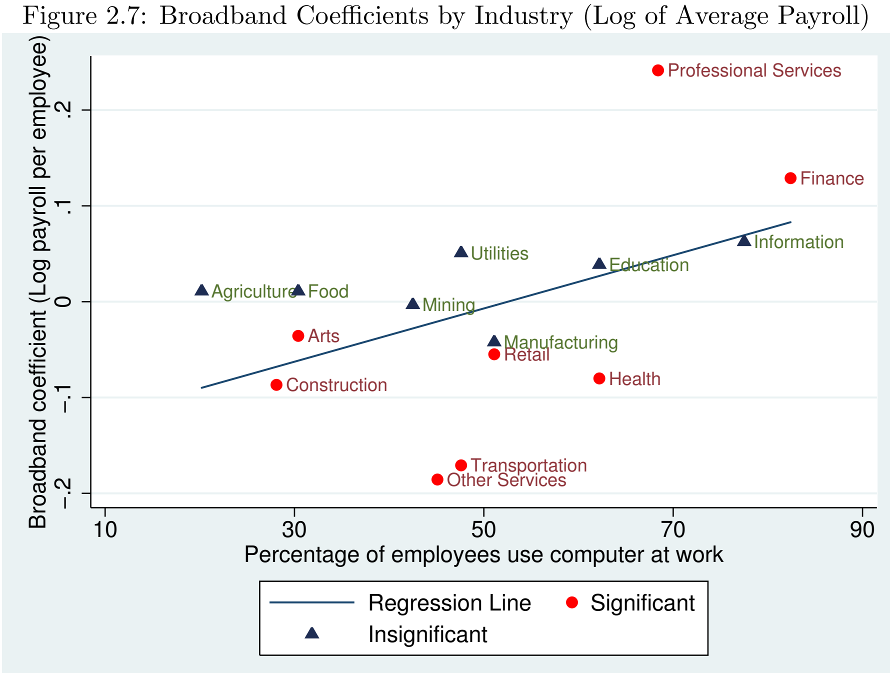


Figure 2.8: Broadband Coefficients by Industry (Log of Average Payroll)

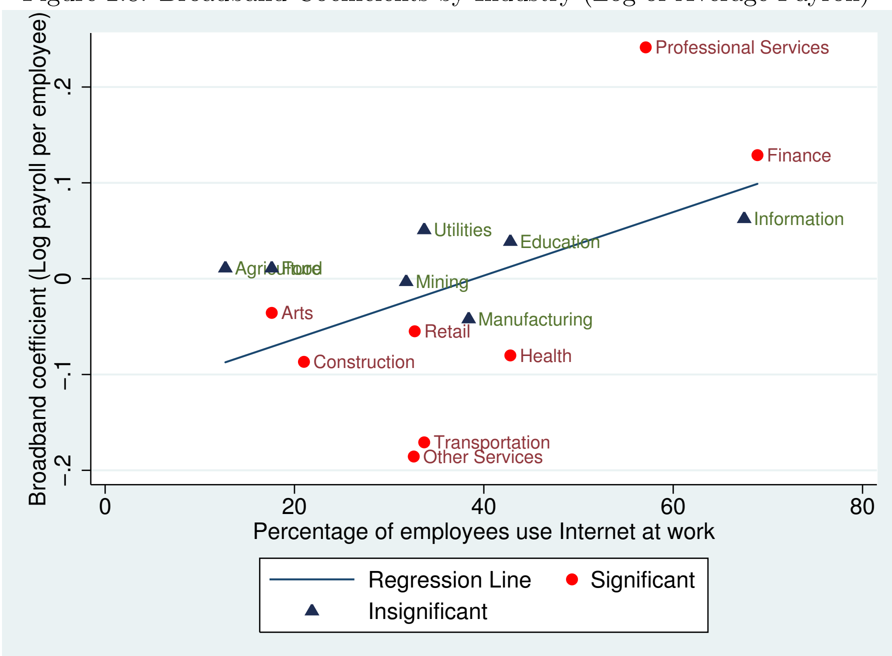


Figure 2.9: Broadband Coefficients by Industry (Log Employee per Establishment)

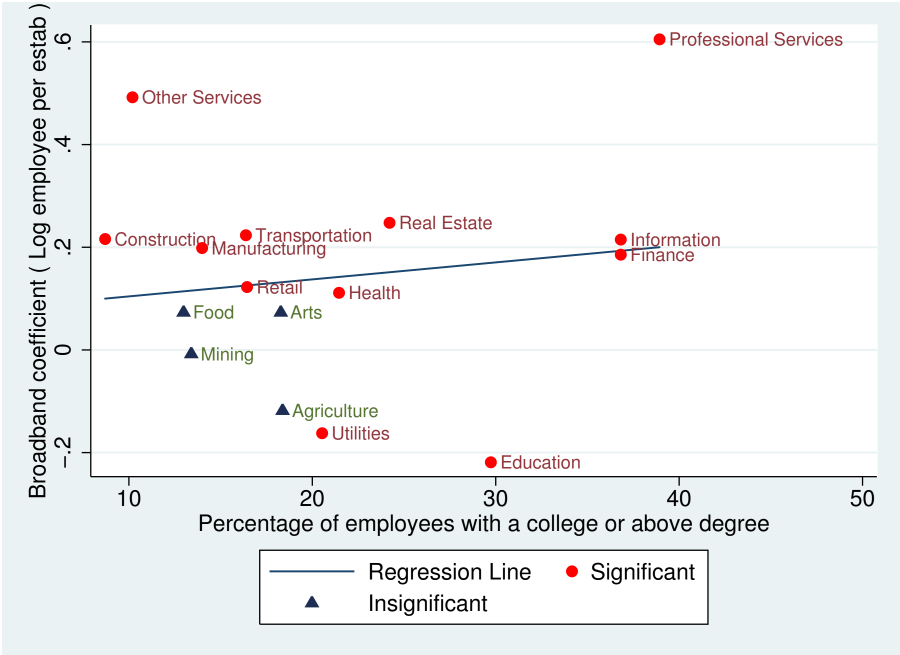


Figure 2.10: Broadband Coefficients by Industry (Log Employee per Establishment)

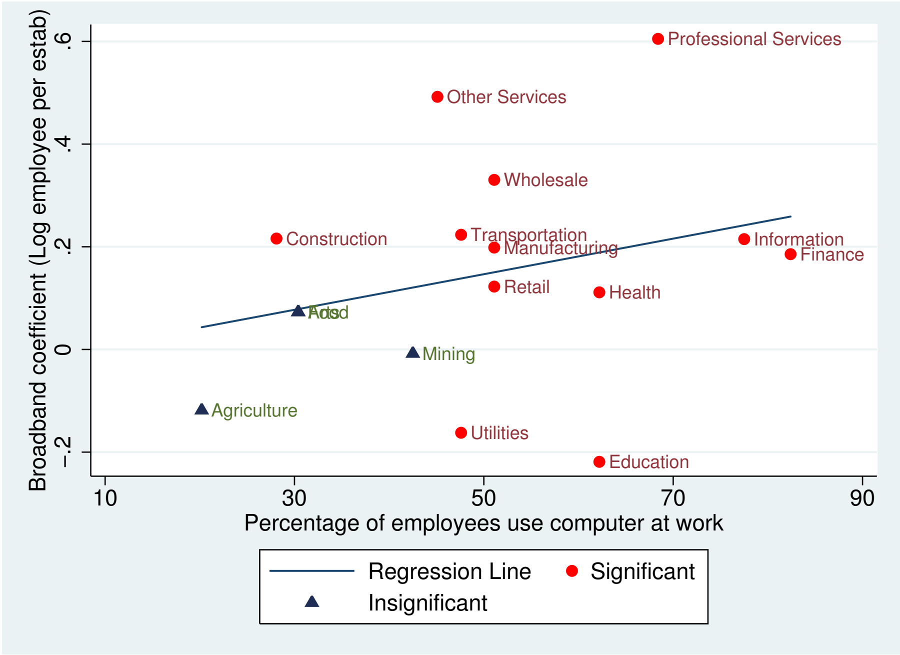


Figure 2.11: Broadband Coefficients by Industry (Log Employee per Establishment)

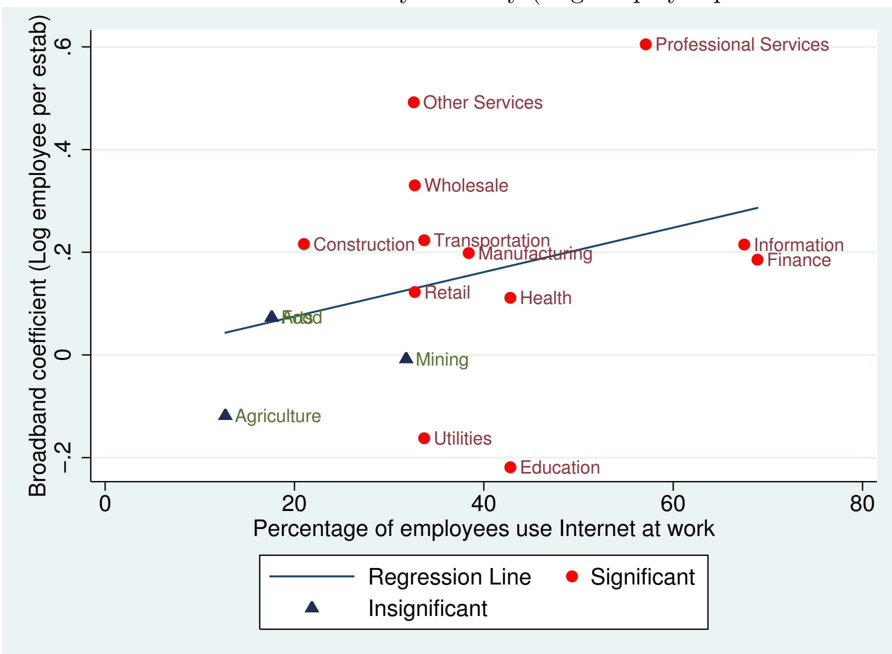


Figure 2.12: Broadband Coefficients by Occupation (Log Employment)

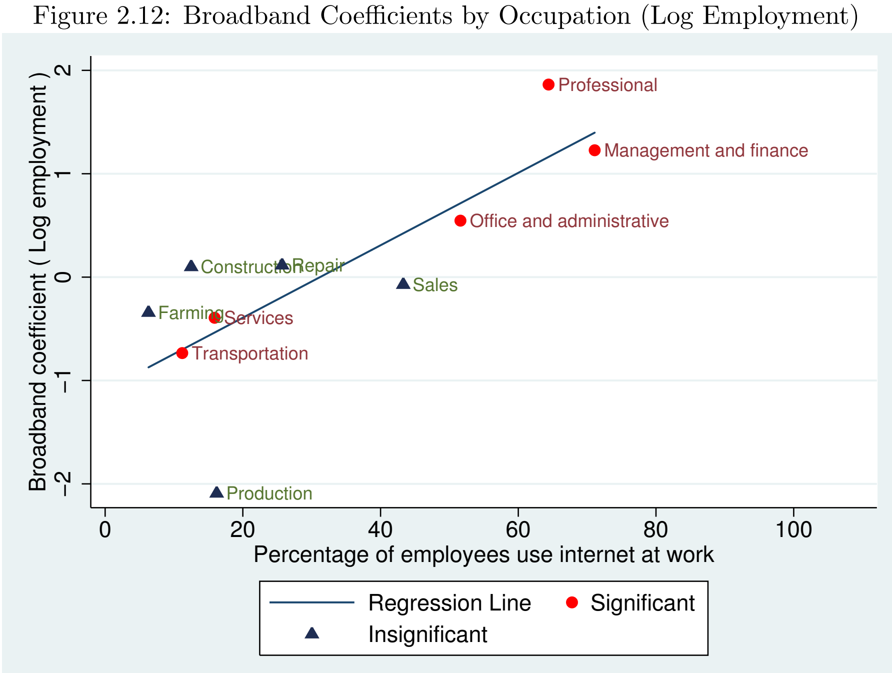
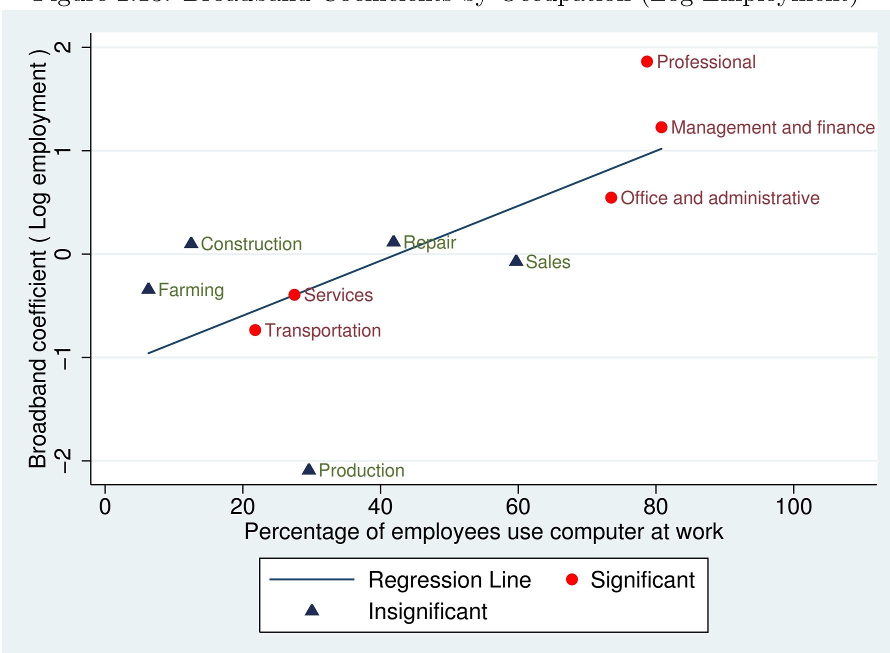


Figure 2.13: Broadband Coefficients by Occupation (Log Employment)



Chapter 3

Information Communication Technology Use and Labor

3.1 Introduction

This paper uses unique data from Turkey to analyze the effects of information communication technologies (ICTs) on firm level employment and wages. Previous studies using data from the United States find evidence that information technologies increase the demand for skilled labor.[1] The effects of ICTs is a more critical issue in developing countries because the impacts have potential to be larger. There can be more significant benefits of ICTs in developing countries since the deployment rate of ICTs are lower.

The main research question in this study is how employment and wages change when firms adopt and use ICTs more intensely. Additionally, I analyze the different mechanisms through which ICTs affect different types of labor. I also investigate if there are different effects on firms of different sectors. I employ unique restricted-use data from Turkey, provided by the Turkish Statistical Institute and the State Planning Organization. This confidential data set includes nationally representative surveys that were conducted from 2007 to 2010 on how much and for what purposes ICTs and the internet are used by firms. These firm level responses to questions about ICT use allow me to go beyond aggregate analysis.

ICTs can change employment levels within the firms through two mechanisms. First, ICTs are skill-biased technologies that change the relative demand for skilled and unskilled labor. ICTs require skilled labor for maintenance and use. Skilled labor also has a higher ability to adapt to new technologies Therefore adoption of these technologies increases the demand and wages for skilled labor. Second, ICTs can lead to expansion by enabling firms to lower costs and penetrate larger geographical markets. Higher production levels due to firm expansion will lead to higher employment levels. The presence of these two mechanisms have different policy implications. The first mechanism will change the skill composition of the labor force within firms and thus increase the skill gap, whereas the second mechanism will not affect the relative demand for skilled and unskilled labor.

[1] Acemoglu (1998), Autor, Katz and Kruger (1998), Autor, Levy and Murane (2001) and Bresnahan, Brynjolfsson and Hitt (2002) find evidence that information technologies are skill biased. Michaels, Natraj and Van Reenen (2010) provide evidence that information communication technologies are skilled biased as well

The survey includes detailed questions on ICT adoption and use. These indicators in the dataset are highly correlated with each other. I summarize these correlated indicators in two different ways: (1) an overall ICT Index that includes adoption, use and skill information and (2) an advanced internet use indicator that focuses on advanced internet applications.

The ICT Index and advanced internet use variables are positively correlated with total employment levels in firm fixed effects models that remove the unobserved heterogeneity at the firm level. The positive correlation between ICTs and employment is due to the relationship between ICTs and ICT-related employment (ICT experts and ICT users). There is no significant relationship between ICTs and non-ICT employment. These results suggest that ICTs have direct effects on ICT-related employment: firms that adopt and use these technologies hire workers in order to maintain and use the new technologies. The scale effects that can increase the demand for non-ICT employment are not significant for the two-year fixed effects models. However, these effects might require longer periods of time to emerge, and this panel might not be long enough for them to be significantly present.

I use four year panel that does not include a full set of control variables to analyze longer term effects. I estimate the effect of lags of ICT measures. Firm fixed effects models show significant effects of ICT measure on non-ICT employment after one year and the magnitude increases after two years. There is a similar pattern for productivity variables as well. Overall, the evidence indicates that in the short term, ICT investment leads to increases only in ICT-related workers. Over a longer period, there are more significant effects on non-ICT employment through scale and productivity effects.

There is an endogeneity problem in analyzing the relationship between ICTs and employment due to reverse causality and self-selection. I address this problem in two ways. First, I use generalized propensity score matching that removes these observable biases. This method calculates the effect of ICTs on employment and wages by only comparing firms that are similar in many dimensions such as industry, location, ownership status, investment, profits, trade balance, and output. I find positive effects of the ICT index on employment and wages within firms, and these effects diminish after a certain level of ICT investment. When the ICT index increases from 0 to 0.8, employment increases by 5 percent while wages increase by 8 percent within the firms. These effects stay constant for ICT index levels 0.8 to 1. Second, I use instrumental variables to obtain further evidence on causality. I find different sets of instruments to be valid for different industries and technology use classifications within the same sector. Instrumental variables and falsification tests provide further evidence that the results are robust.

3.2 Data

The Turkish Statistical Institute and the State Planning Organization conducted ICT adoption and use surveys from 2007-2010. These survey data include detailed questions about how much and for what purposes ICTs are used within firms. They are nationally representative in each year. This data set is restricted-use since it includes confidential information about the firms and can be only accessed at the Data Research Center of the Turkish Statistical Institute in Ankara, Turkey.

I match ICT use data with business statistics and trade data in order to obtain a full set of control variables of the firms. The business statistics data include detailed information about employment, production, profit, investments, location, sector, capital stock and composition, ownership, branches, and other important firm characteristics. The trade data set includes information on the imports and exports made by each firm and their trade partners. Business statistics are only available for 2007 and 2008 as of now.[2]. The ICT survey has 3,364 observations from 2007 and 4,601 observations from 2008. This survey is an unbalanced panel; some of the firms are surveyed over multiple years. Matching ICT, business, and trade datasets results in a dataset of 5,570 observations over 2007 and 2008. I also use a four-year panel that does not include the full set of control variables for some part of the analysis. Here, I use the balanced panel of 454 firms over four years with a total of 1,816 observations.

There are many ICT adoption and use indicators in the data set, and they are highly correlated with each other. Including these indicators separately in regressions leads to serious multicollinearity problems, therefore I summarize this information into two different measures: the ICT index, and the advanced internet use indicator. The first variable is an overall index that summarizes ICT adoption and use indicators, while the second variable concentrates on the ICT use intensity.

The ICT index is a weighted average of ICT adoption, use, and skill measures. The ICT adoption indicators include presence of computers and the internet as well as the speed level of the internet connection (ISDN, ADSL, cable, or mobile). Some of the ICT use indicators are: employing these technologies for enterprise resource planning, supply chain management, customer relationship management, e-commerce, etc. Finally, the ICT skill indicators are measures of employees knowledge about these technologies, the share of employees who use the internet, the share of employees with ICT training, and the availability of ICT education for employees. First, I calculate ICT adoption, use and skill indices weighing each indicator equally within the groups. Then I combine these three indices into a single ICT Index. I weigh the three indicators based on the International Telecommunication Societys ICT Development Index weights.[3] According to this

[2] 2009 and 2010 will be added as they become available

[3] International Telecommunications Union Report (2009)

index, ICT adoption is weighted by 40 percent, ICT use is weighted by 40 percent, and ICT skill is weighted by 20 percent. The ICT index is between 0 and 1, with 0 meaning no ICTs in effect and 1 meaning full use of ICTs within the firms. I use different weights in order to check for robustness. The results are robust to different weights.

The second measure of ICTs concentrates on advanced internet applications. The advanced internet use indicator shows whether firms use at least 3 of the following ICT applications that are known to affect organizational change and inter-establishment communication:[4]

1. Enterprise Resource Planning
2. Supply Chain Management
3. Customer Relationship Management
4. Education
5. Purchasing
6. Customer Support
7. Extranet

The results are robust to using different combinations of these internet applications.

Table 3.1 presents summary statistics of some of the dependent and business variables in the final data set. Means and standard deviations of employment, wages, and some control variables are listed. The average employment level is 460 where around 75 percent of the employees are male. Control variables include profits, costs, revenue, production, investment, capital stock, the ratio of capital owned by foreign direct investment, imports, exports, the number of establishments within the same firm, and other business statistics.

Table 3.2 presents the summary statistics for ICT variables. The ICT Index and advanced internet use are variables that are calculated in order to measure the ICT levels within the firms. The variables represent the share of firms using each application. The share of the firms have computers is 96 percent and 83 percent have broadband connections. The other summary statistics are the average ratio of firms using listed ICT applications. The share of firms engage in e-commerce is 23 percent and 62 percent of firms use ICTs for marketing purposes. Forty two percent of firms use ICTs for training and educational purposes. Other commonly used applications are online banking, online transactions and e-government.

[4]Forman, Goldfarb and Greenstein (2012)

3.3 Empirical Specification and Results

I use the following basic model for empirical specification:

$$\text{Log(employment)}_{it} = \beta_0 + \beta_1 \text{ICT Index}_{it} + \delta X_{it} + \alpha_i + \lambda_t + \epsilon_{it} \tag{3.1}$$

where $\text{Log(employment)}_{it}$ is the log of employment in firm i at time t, ICT Index_{it} is the ICT Index of firm i at time t, X_{it} includes firm controls such as value-added, capital, exports, imports, R&D expenditure, patents. The firm fixed effects term that absorbs any permanent heterogeneity at the firm level is α_i. The time control that absorbs time specific shocks shared by all the firms is λ_t.

Table 3.3 presents the OLS and firm fixed effects regressions where the dependent variable is log of employment. In column 2, the OLS regression controls for city, sector, year, capital stock, value-added, export value, import value, R&D expenditure, share of revenue from services, and trade. In column 4, the firm fixed effect model also controls for business and trade statistics, except city and sector that are fixed for firms. The rest of the tables control for the same firm characteristics. In the OLS model with a full set of controls, the coefficient of the ICT Index suggests that employment increases by 3.5 percent within the firms when their ICT index moves from 0 to 1. In the firm fixed effects regressions, the coefficient drops to 0.4 percent.

Table 3.4 presents OLS and fixed effects results where the dependent variable is log of wages per employee in each firm. A higher ICT Index is also associated with higher average wages. Again, the magnitudes of the coefficients are smaller when firm heterogeneity is controlled for.

The positive effects of ICTs on employment can be due to two mechanisms: an increase in ICT employees with the adoption of new technologies, and overall expansion in the firm. Next, I analyze the effects of ICTs on different types of labor to obtain evidence of the presence of these mechanisms. There are two categories listed in the data set for ICT-related employment: ICT experts and ICT users. ICT experts are the employees who maintain the networks and databases. ICT users are the employees who use the ICT systems and applications.

Table 3.5 presents the ICT index coefficients on ICT employment (ICT experts and users) and non-ICT employment in the firm (employment other than ICT experts and ICT users) from fixed effects regressions. The coefficient of the ICT index on log of ICT employment is 0.9 and significant. The coefficient on log of non-ICT employment is insignificant. This implies that the positive relationship between ICTs and overall employment is due to ICT-related employment and not the remaining employment in the firm fixed effects regressions.

When I repeat the OLS and fixed effects regressions using advanced internet use dummy instead of the ICT Index, I obtain slightly higher coefficients on log of employment and ICT employment. Table 3.6 reports the firm fixed effects regression results where the independent variable for ICTs is advanced internet use. These results control for basic internet (non-broadband internet connections) and the presence of computers, as well as other firm characteristics, in order to ensure the relationship between advanced internet use and employment is not due to the presence of computers or internet.

Using both the ICT Index and advanced internet use measures, there is significant positive relationship between ICTs and ICT employment and non-significant relationship between ICTs and non-ICT employment. The positive effects of ICTs on ICT employment is not surprising; the firms that adopt and use these technologies more heavily need labor in order to deploy, use, and maintain them. The two year panel data might be too short for the scale effects to take place. Increases in productivity and production would lead to increases in employment, but these changes are hard to observe over a year.

Next, I use the four year panel data (2007-2010) in order to estimate ICT effects on labor over a longer time period. I lack the control variables for 2009 and 2010, and I only include the firm's initial values of control variables. Table 3.7 presents the results where log ICT employment and log non-ICT employment are regressed on the first and second lags of ICT index and advanced internet use. The first and second lags of ICT variables are significant for the fixed regressions where the dependent variable is log ICT employment. The effects of ICTs on ICT employment diminish over time. On the other hand, the effects on non-ICT employment are significant using the lagged ICT variables, and the magnitude increases over time. These results support that ICT investments lead to an increase in ICT workers for a while, and this effect decreases over time. The initial setup and use of these technologies might require more labor. ICT investments can only increase other types of employment after a couple years, since this mechanism is indirect. The increases in productivity and geographical market do not happen immediately, so we observe the effects of ICT investments on non-ICT workers only using the lagged ICT measures.

Related to the longer term effects of ICTs on non-ICT labor, I analyze the effects on firm productivity. I use output per employee and value-added per employee as two measures of firm productivity. Table 3.8 presents the results where the dependent variable is log output per employee in column 1 and log value-added per employee in column 2. There ICT measures and the productivity measures are not significantly correlated in the two-year panel. Table 3.9 presents the results of effects of lags of ICT measures on the productivity measures in the four-year panel. Similar to the non-ICT employment results, the coefficients are significant and they increase over time. These results support the idea that ICTs take couple of years to lead to productivity gains that can increase the demand for non-ICT employment.

3.4 Generalized Propensity Score Matching

I use the generalized propensity score (GPS) matching method to predict the ICT Index based on observable characteristics such as profits, production, capital, ownership, sector, location, revenue, investment, loss, number of branches, and other business statistics. Generalized propensity score is developed by Imbens and Hirano (2004) and Imai and Van Dyke (2004) as an extension of propensity score by Rosenbaum and Rubin (1983). The generalized propensity score extends the propensity score for binary treatments to continuous treatment variables. The idea is to match the firms that are the most similar along several characteristics that determine ICT index level and employment level. This method eliminates the bias associated with differences in observable covariates.

The first step is to estimate the conditional density of the treatment given the covariates,

$$r(t, x) = f_{T|X}(t|x) \tag{3.2}$$

where T is the treatment level (ICT Index in this case) and X are the observable covariates. The generalized propensity score is $R = r(T|X)$. The next step is to estimate the conditional expectation of the outcome (employment) as a function of the treatment level T (ICT Index) and GPS level R (Estimated ICT Index),

$$\beta(t, r) = E[Y|T = t, R = r] \tag{3.3}$$

To estimate the dose-response function at a particular level of treatment, I average this conditional expectation over the GPS at a particular level of ICT Index (which is denoted by t) ,

$$\mu(t) = E[\beta(t, r(t, x))] \tag{3.4}$$

To see whether this specification of the propensity score is adequate, I investigate how it affects the balancing of covariates. To test for the balancing of covariates, I divide the ICT Index into 3 ranges and test whether the adjusted means in each group is different from the other 2 groups. Covariates are not balanced when unadjusted, meaning the firms that have different levels of ICT index differ in the covariates. These observable covariates are balanced when adjusted for GPS. The means of covariates are not statistically different from each other among the 3 ranges of ICT Index levels. This indicates that the GPS method is able to correct for any observable heterogeneity between the firms.

Figure 3.1 presents the dose-response function estimated by the generalized propensity score method. Here, the ICT Index levels range from 0 to 100, indicating the percentage of ICT adoption and use intensity.

The effect of the ICT Index increases up to a level of 80 percent, where the effect is maximized with a 5% increase in employment level. Then the coefficient remains around 5% between ICT Index levels of 80 to 100 percent.

Figure 3.2 presents the dose-response function estimates of the effects of the ICT Index on wages. The ICT Index causes an increase of between 9-10% in wages, and this relationship increases linearly. I also estimate a similar function for ICT adoption, use, and skill indices separately.

Next, I divide total employment into ICT-related and non-ICT employment. Figure 3.3 presents the dose-response function estimates of the effects of the ICT index on ICT employment. The effect of the ICT Index on ICT employment ranges is around 4 percent at the lower level of the ICT Index, and this effect goes up to 5.5 percent at the top levels of the ICT Index. The second part of Figure 3 presents the treatment effect function which shows the effects on differences between current ICT employment and ICT employment in the previous period. Figure 3.4 presents the dose response function and the treatment effect function of the ICT index on log of non-ICT employment. The effect on non-ICT employment goes up to 1 percent for firms that have a 100 percent ICT index.

3.5 Instrumental Variables

I use instrumental variables in order to predict firm level advanced internet use. After using them for all the firms, I separate the firms by industries, since it is unlikely that these instruments are valid for all type of firms.

First, I use 5 different instruments for firm level advanced internet use for all firms:

1. The city level ICT adoption index of all firms minus the firm in each observation (an index between 0 and 1)
2. Whether the firm has an outsourcing opportunity of ICT tasks at a branch of the firm located in a different country
3. The city level broadband penetration rate (between 0 and 100 percent)
4. Whether the firm is located in one of the cities where the first internet connection was available in Turkey in 1994
5. Whether the firm is located in a city that has fiber optic internet technology.

Table 3.10 presents the instrumental variable estimation results. Here, I use the two year panel that includes full control variables. The first stage regressions all have high explanatory power and significant coefficients of instruments on advanced internet use dummy. The second stage regressions are presented for three dependent variables. The results are significant for ICT employment and average wages per employee. The coefficients on non-ICT employment are not significant in the IV estimation. The standard errors are corrected for the panel observations and for heteroskedasticity.

Next, I test for the validity of the instruments by using different combinations of instruments for different sectors. City level internet deployment variables are not good instruments for industries where firm location is endogenous. On the other hand, they can be good instruments for sectors that are present in all cities. Firm level outsourcing at a foreign branch variable is not a good instrument for industries in which it is uncommon to have a branch in a different country. I use 4 different groups to test this:

1. Manufacturing: These firms choose the city location, and it is likely that they have a foreign branch.
2. Services: These are usually firms of local services that are present in every city, and it is not likely that they have a foreign branch.
3. Wholesale: This is a big very industry in Turkey, as there are not many large supermarkets/stores. These firms distribute to all the neighborhood stores. These firms are located in all cities with no foreign branch.
4. Exporting Firms : These are the firms that do exporting regardless of their sector. These firms usually have foreign branches, and their location is endogenous.

I used different combination of instruments and sectors for specification tests. The assumption that the instruments are not correlated with the error term in the equation of interest is not testable in exactly identified models. If the model is overidentified, there is information available which may be used to test this assumption. The most common test of these overidentifying restrictions, is based on the observation that the residuals should be uncorrelated with the set of exogenous variables if the instruments are truly exogenous.[5] I used over-identifying restrictions test and orthogonality test in order to decide whether a set of instruments is valid. The results coincide with the intuition that not all the instruments are valid for all industries. The city level instruments work for the sectors that have to be present in every city. The outsourcing instrument does not work for these sectors since they usually do not have foreign branches. On the other hand, the outsourcing instrument works well for the manufacturing sector and exporting firms. When the city level instruments are added, the set of instruments become invalid since these firms choose their location. Table 3.11 summarizes the sets of IVs that are valid based on the above tests.

[5] Sargan (1958)

Table 3.12 presents the IV estimation results with the valid IV specification for each sector. All combinations of the instruments presented have strong first stage results, with high F-statistics and no weak and under identification based on tests, with an exception of the services sector.

There is significant within-sector heterogeneity. I further divide the manufacturing and services industries into smaller groups in order to remove some of the relevant heterogeneity within the sectors. I classify the manufacturing firms as high-tech and low-tech, and the services firms as knowledge-intensive and less knowledge-intensive based on OECD Nace Rev 1.1 industry codes.

Table 3.13 shows the valid instruments for different sector classifications based on the specification tests. Table 3.14 presents the instrument variable estimation results using the valid set of instruments for each industry classification. There are further differences in between high-tech manufacturing and low-tech manufacturing firms, and especially between knowledge-intensive and less knowledge-intensive services firms. Location instruments work better for low-tech manufacturing firms and less-knowledge intensive services firms.

3.6 Robustness Checks

I use past variables of business and trade statistics of the firms taken between 2003 and 2006 (the current data set is for 2007 and 2008) for falsification tests. In order to see whether the relationship between advanced internet use and employment is due to some other unobservable factors, I regress current advanced internet use levels on past employment levels. In column 1 of Table 3.15, the dependent variable is advanced internet use, and in column 2 the dependent variable is ICT index. Past employment levels do not predict current ICT levels. This evidence supports the causal interpretation from ICTs to employment.

If the relationship between advanced internet use and ICT employment is due to some unobservable factors, we might expect to see an accidental significant relationship with other employment variables as well. Table 3.16 presents the regressions where dependent variables are R&D employment, part-time employment, and hours worked. There are no significant effects of advanced internet use on R&D employment, part-time employment, and hours worked.

The data set includes information on whether the firm hired one or more ICT employee(s) (ICT experts and ICT users) within the last year. There is no information on how many people they have hired for these jobs. Table 3.17 presents probit regressions of dummy variables for whether the firm hired ICT experts and ICT users on advanced internet use. These probit regressions control for all the firm characteristics. There are also questions about types of problems the firm has encountered in the process of hiring ICT experts.

These problems are: absence of enough candidates, absence of educated candidates, absence of experienced candidates, and high wage demands of candidates. Not all the firms answered this question, so the sample size drops in the last column. With additional controls for these factors, the firms that use advanced internet applications are 60 percent more likely to hire a new ICT expert. This also supports the mechanism of firms hiring new ICT workers to maintain the technology.

3.7 Conclusion

This paper analyzes how ICT adoption and use affect employment and wages within firms. I use a confidential data set provided by the provided by the Turkish Statistical Institute and the State Planning Organization. Detailed surveys were conducted from 2007-2010 on how much and for what purposes ICTs and the internet are used by individuals and firms. I summarize several ICT adoption and use indicators into an ICT Index to measure how intensely these technologies are utilized within each firm. I also analyze these ICT indicators separately.

In addition to OLS and fixed effects models, I use the generalized propensity score matching method in order to control for the observed heterogeneity between firms. I find a significant positive association between ICT use intensity, employment and wages within the firms.

The positive effects of ICTs on employment can be due to two mechanisms: the increase in ICT employees with the adoption of new technologies, and overall expansion in the firm. I test for the presence of these mechanisms by dividing the total employment into ICT and non-ICT employment. ICT use increases ICT employment especially in the short term, and this effect seems to diminish over time. On the other hand, ICT use does not significantly change non-ICT employment in the 2 year fixed effects models, but there are significant and increasing effects in the 4 year fixed effects models. These results suggest that ICT investments lead to firm expansion not immediately but over a longer period. Instrumental variable estimations and falsification tests supports the causal direction from ICT investments to employment.

3.8 Tables and Figures

Table 3.1: Summary Statistics

Employment, Business and Trade Statistics

	Mean	Standard Deviation
Employment	459.24	1424.62
R&D Employment	4.58	40.97
Female Employees	110.75	346.25
Male Employees	348.14	1193.12
Weekly hours worked	44.95	2.71
Total Wages (in million TL)	1.02	0.51
Total Payment (in million TL)	12.42	56.45
Total Cost (in million TL)	135	768
Total Revenue (in million TL)	158	850
Profits (in million TL)	8.63	80.8
Loss (in million TL)	2.71	25.9
Investment (in million TL)	5.04	11.7
Value Added (in million TL)	28.1	159
Capital (in million TL)	4.73	3.64
R&D Expenditures (in million TL)	0.15	2.87
Patent Value (in million TL)	0.34	4.05
Export Value (in million TL)	29.2	414
Import Value(in million TL)	12.9	146

Table 3.2: ICT Summary Statistics

ICT Adoption and Use Statistics

	Mean	Standard Deviation
ICT Index	0.6142	0.1924
Advanced Internet Use	0.3682	0.4823
Presence of computers	0.9657	0.1819
Presence of broadband	0.8364	0.2439
Employees using computers	124.12	470.25
Employees using internet	94.682	378.43
Enterprise Resource Planning	0.2850	0.4514
Customer Relationship Management	0.1994	0.3996
Supply Chain Management	0.1428	0.3499
Purchasing	0.4361	0.4959
Education	0.4266	0.4946
Webpage Customer Support	0.2749	0.3472
Extranet	0.1745	0.2763
E-commerce	0.1232	03754
E-government	0.6931	0.4613
E-banking	0.8645	0.3422
E-commerce	0.2323	0.1735
E-government	0.7993	0.4005
Has a webpage	0.7476	0.4344
Marketing	0.6224	0.4849
Inventory	0.5828	0.4932
Training	0.1662	0.3723
Payments	0.4709	0.4999
Security software use (among e-commerce firms)	0.9942	0.0758

Table 3.3: OLS and Fixed Effects

Dependent Variable: Log employment

	OLS	OLS full controls	Fixed effects	Fixed effects full controls
ICT Index	1.5029***	1.4626***	0.3128**	0.3591**
	(0.0840)	(0.0820)	(0.1539)	(0.1539)
Industry Fixed Effects	Yes	Yes	No	No
City Fixed Effect	Yes	Yes	No	No
Firm Fixed Effects	No	No	Yes	Yes
Observations	5570	5570	5570	5570

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Control variables included: year, capital stock, value-added, export value, import value, R&D expenditure, share of revenue from services, and trade.

Table 3.4: OLS and Fixed Effects

Dependent Variable: Log wages				
	OLS	OLS full controls	FE	FE full contols
ICT Index	0.5797***	0.5788***	0.3353**	0.2628*
	(0.0667)	(0.0667)	(0.1504)	(0.1492)
Industry Fixed Effects	Yes	Yes	No	No
City Fixed Effect	Yes	Yes	No	No
Firm Fixed Effects	No	No	Yes	Yes
Observations	5570	5570	5570	5570

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Control variables included: year, capital stock, value-added, export value, import value, R&D expenditure, share of revenue from services, and trade.

Table 3.5: ICT employment and Non-ICT employment

	ICT employment	Non-ICT employment
ICT Index	0.9238***	0.2178
	(0.2846)	(0.1427)
Firm Fixed Effects	Yes	Yes
Full Controls	Yes	Yes
Observations	5570	5570

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Control variables included: year, capital stock, value-added, export value, import value, R&D expenditure, share of revenue from services, and trade.

Table 3.6: Advanced internet Use

	Log Employment	Log ICT Employment	Log Non-ICT Employment	Wages
Advanced Internet Use	0.5136***	1.0572***	0.0971	0.4981***
	(0.0640)	(0.0946)	(0.0719)	(0.0221)
Firm Fixed Effects	Yes	Yes	Yes	Yes
Full Controls	Yes	Yes	Yes	Yes
Observations	5570	5570	5570	5570

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Control variables included: year, capital stock, value-added, export value, import value, R&D expenditure, share of revenue from services, and trade.

Table 3.7: Four Year Panel: 2007-2010

Dependent Var: Log ICT Employment

	(1)	(2)	(3)	(4)
Lag 1 ICT Index	1.2542***			
	(0.1440)			
Lag 2 ICT Index		0.8326***		
		(0.2428)		
Lag 1 Advanced Internet Use			0.5163***	
			(0.0789)	
Lag 2 Advanced Internet Use				0.1344**
				(0.0517)

Dependent Var: Log Non-ICT Employment

	(1)	(2)	(3)	(4)
Lag 1 ICT Index	0.1153			
	(0.3034)			
Lag 2 ICT Index		0.2524*		
		(0.1362)		
Lag 1 Advanced Internet Use			0.1692**	
			(0.0860)	
Lag 2 Advanced Internet Use				0.3167*
				(0.1793)
Fixed Effects	Yes	Yes	Yes	Yes
Full Controls	No	No	No	No
Observations	1362	1362	908	908

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.8: Regressions of productivity measures

	(1) Log output per employee	(2) Log value-added per employee
ICT Index	0.0554	0.0812
	(0.0610)	(0.1069)
Advanced Internet Use	0.0227	0.0719
	(0.0384)	(0.0871)
Firm Fixed Effects	Yes	Yes
Observations	5570	5570

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.9: Lags of ICT variables

Dependent Var: Log output per employee

	(1)	(2)	(3)	(4)
Lag 1 ICT Index	0.2031***			
	(0.0590)			
Lag 2 ICT Index		0.6040***		
		(0.0876)		
Lag 1 Advanced Internet Use			0.1167***	
			(0.0279)	
Lag 2 Advanced Internet Use				0.4921***
				(0.0319)

Dependent Var: Log value-added per employee

	(1)	(2)	(3)	(4)
Lag 1 ICT Index	0.2832***			
	(0.0988)			
Lag 2 ICT Index		0.7571***		
		(0.0939)		
Lag 1 Advanced Internet Use			0.2247***	
			(0.0758)	
Lag 2 Advanced Internet Use				0.6818***
				(0.0718)
Fixed Effects	Yes	Yes	Yes	Yes
Full Controls	No	No	No	No
Observations	1362	1362	908	908

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.10: Instrumental Variable Estimation

First Stage Regressions					
Dependent Variable: Advanced Internet Use					
Instruments	city ict adoption	ict at foreign branch	city broadband penetration	first internet	fiber optic access
city ict adoption	3.4121***				
	(0.1376)				
ict at foreign branch		0.3350***			
		(0.0115)			
city broadband penetration			0.0024***		
			(0.0001)		
first internet access				0.0361***	
				(0.0039)	
fiber optic access					0.0365***
					(0.0041)
F-statistics	72.07	86.14	142.30	131.27	131.12
Second Stage Regressions					
Instruments	city ict adoption	foreign branch	city broadband penetration	first internet	fiber
Dependent Variable: Log ICT Employment					
Advanced Internet Use	0.1204***	0.78341***	1.5670***	2.3252***	2.2663***
	(0.0351)	(0.0500)	(0.0921)	(0.2559)	(0.2549)
Dependent Variable: Log Wages					
Advanced Internet Use	1.2792**	1.5277***	1.6685***	3.5229***	3.0256***
	(0.5276)	(0.3719)	(0.3555)	(0.9898)	(0.7634)
Dependent Variable: Log Non-ICT Employment					
Advanced Internet Use	-0.0611	-0.0313	0.1701	0.2961	0.2302
	(0.0701)	(0.0715)	(0.1077)	(0.2080)	(0.1921)
Observations	5570	5570	5570	5570	

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Control variables included: year, capital stock, value-added, export value, import value, R&D expenditure, share of revenue from services, and trade.

Table 3.11: Validity of IVs for different sectors

	Manufacturing	Services	Wholesale	Exporting
City level firm ICT adoption index	×	✓	✓	×
Outsourcing of ICTs at a foreign	✓	×	×	✓
City broadband penetration rate	✓	✓	✓	✓
City with a first internet 1994	×	✓	×	×
City with fiber	×	✓	✓	×

Table 3.12: IVs for different sectors

First Stage Regressions: Dependent Variable is Advanced Internet Use

	Manufacturing	Services	Wholesale	Exporting
city ict adoption		0.3855**	0.3965**	
		(0.2098)	(0.1971)	
outsource at foreign branch	0.2611***			0.1760***
	(0.0394)			(0.0383)
city broadband penetration	0.0011**	0.0014**	0.0010**	0.0015**
	(0.0006)	(0.0007)	(0 .0006)	(0.0008)
first internet access		0.0587*		
		(0.0368)		
fiber optic access		0.0189***	0.0315***	
		(0.0077)	(0.0124)	
Observations	2703	1040	2060	1702
F-statistics	25.94	10.74	22.84	26.90

Second Stage Regressions

Dependent Variable: Log ICT Employment

	Manufacturing	Services	Wholesale	Exporting
Advanced Internet Use	1.4496***	3.1850**	1.7962***	0.9886**
	(0.2738)	(1.5066)	(0.3610)	(0.4510)

Dependent Variable: Log Wages

	Manufacturing	Services	Wholesale	Exporting
Advanced Internet Use	1.2598***	2.9476**	1.6226***	1.3308***
	(0.5138)	(1.4567)	(0.3377)	(0.4021)

Dependent Variable: Log Non-ICT Employment

	Manufacturing	Services	Wholesale	Exporting
Advanced Internet Use	0.3178	0.4625	-0.0438	-0.0359
	(0.2829)	(0.5085)	(0.3536)	(0.3250)

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Control variables included: year, capital stock, value-added, export value, import value, R&D expenditure, share of revenue from services, and trade.

Table 3.13: Validity of IVs for manufacturing and services sectors

	High-tech manufacturing	Low-tech manufacturing	Knowledge-int services	Less knowledge-int services
City level firm ICT adoption index	×	×	×	✓
Outsourcing of ICTs at a foreign	✓	✓	✓	×
City broadband penetration rate	✓	✓	✓	✓
City with a first internet 1994	×	×	×	✓
City with fiber	×	✓	×	✓

Table 3.14: IVs for manufacturing and services

First Stage Regressions: Dependent Variable is Advanced Internet Use

	High-tech manufacture	Low-tech manufacture	Knowledge-intensive services	Less knowledge-intensive services
city ict adoption				1.5330***
				(0.5783)
outsource at foreign branch	0.1757***	0.3428***	0.3588***	
	(0.0681)	(0.0860)	(.0718)	
city broadband penetration	0.0099**	0.0021**	0.0019*	0.0038**
	(0.0039)	(0.0010)	(0.0008)	(0.0017)
first internet access				0.0974*
				(0.0578)
fiber optic access		0.1476**		0 .1763**
		(0.0737)		(0.0737)
Observations	538	1116	336	704
F-statistics	12.34	15.89	8.52	19.17

Second Stage Regressions

Dependent Variable: Log ICT Employment

	High-tech manufacture	Low-tech manufacture	Knowledge-intensive services	Less knowledge-intensive services
Advanced Internet Use	2.5190***	1.1891***	0.9741**	1.6027***
	(0.9175)	(0.3706)	(0.4625)	(0.3730)

Dependent Variable: Log Wages

Advanced Internet Use	1.3272***	1.0593***	1.4660***	1.6990***
	(0.5044)	(0.3656)	(0.4810)	(0.3950)

Dependent Variable: Log Non-ICT Employment

Advanced Internet Use	1.8776**	0.5435	0.3810	0.5807
	(0.7849)	(0.5039)	(0.5549)	(0.4127)

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Control variables included: year, capital stock, value-added, export value, import value, R&D expenditure, share of revenue from services, and trade.

Table 3.15: Past Employment

	Advanced Internet Use	ICT Index
Log 2003 Employment	0.0114	-0.0041
	(0.0122)	(0.0034)
Log 2004 Employment	0.0041	0.0036
	(0.0109)	(0.0032)
Log 2005 Employment	0.0083	0.0043
	(0.0098)	(0.0035)
Log 2006 Employment	-0.0027	0.0025
	(0.0098)	(0.0030)
Firm Fixed Effects	Yes	Yes
Observations	5570	5570

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.16: Other Labor Variables

	Log R&D Employment	Log Part-Time Employment	Log Hours Worked
Advanced Internet Use	-0.0283	-0.0003	-0.0007
	(0.0448)	(0.0606)	(0.0035)
ICT_Index	0.1838	0.0367	0.0103
	(0.2178)	(0.2412)	(0.0140)
Firm Fixed Effects	Yes	Yes	Yes
Observations	5570	5570	5570

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.17: Probit for ICT hire

	Hired ICT User	Hired ICT Expert	Hired ICT Expert	Hired ICT Expert
Advanced Internet Use	0.7143***	0.7428***	0.7175***	0.5907***
	(0.0461)	(0.0410)	(0.0423)	(0.1675)
Had a problem hiring ICT worker			-0.0429	
			(0.0921)	
Not enough number of candidates				-0.1839*
				(0.1054)
Not enough educated candidates				-0.1330
				(0.1905)
Not enough experienced candidates				0.1199
				(0.2246)
High wage demand of candidates				-0.0727
				(0.1635)
Industry Fixed Effects	Yes	Yes	YesYes	
City Fixed Effects	Yes	Yes	Yes	Yes
Full Controls	Yes	Yes	Yes	Yes
Observations	5570	5570	5532	1133

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Control variables included: year, capital stock, value-added, export value, import value, R&D expenditure, share of revenue from services, and trade.

Figure 3.1: Generalized Propensity Score: Dependent Var is Log of Employment

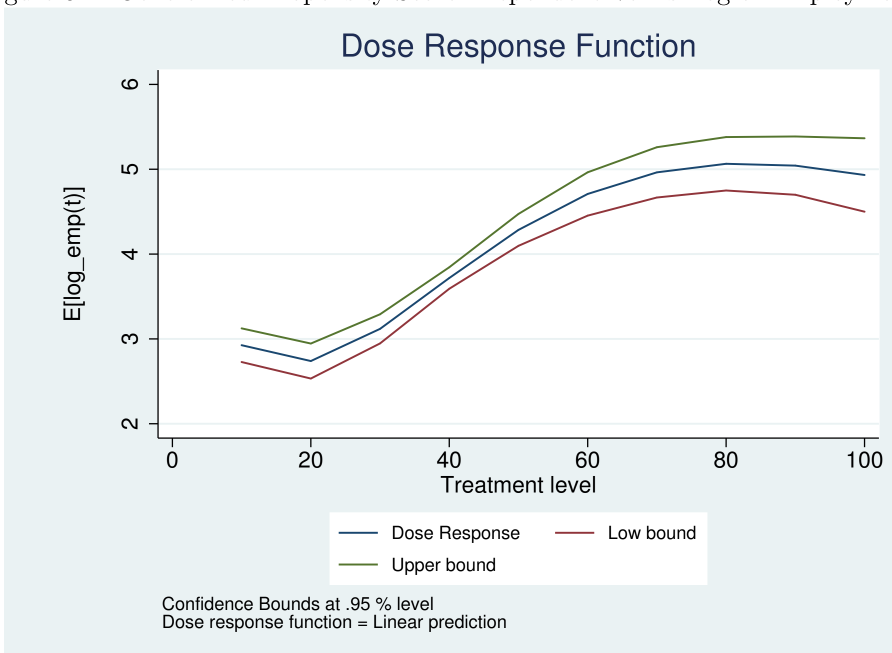


Figure 3.2: Generalized Propensity Score: Dependent Var is Log of Wages

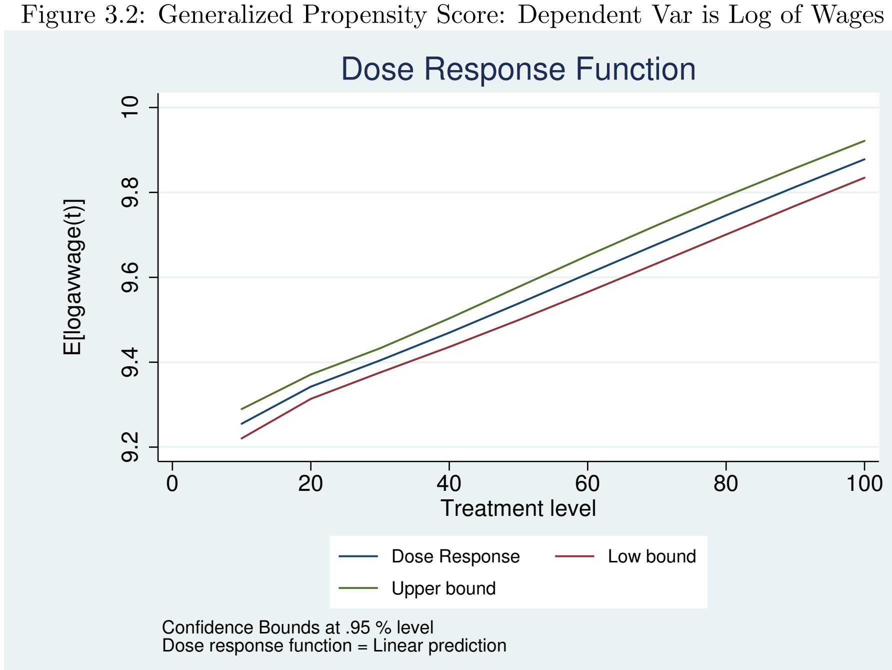


Figure 3.3: Generalized Propensity Score: Dependent Var is Log of ICT Employment

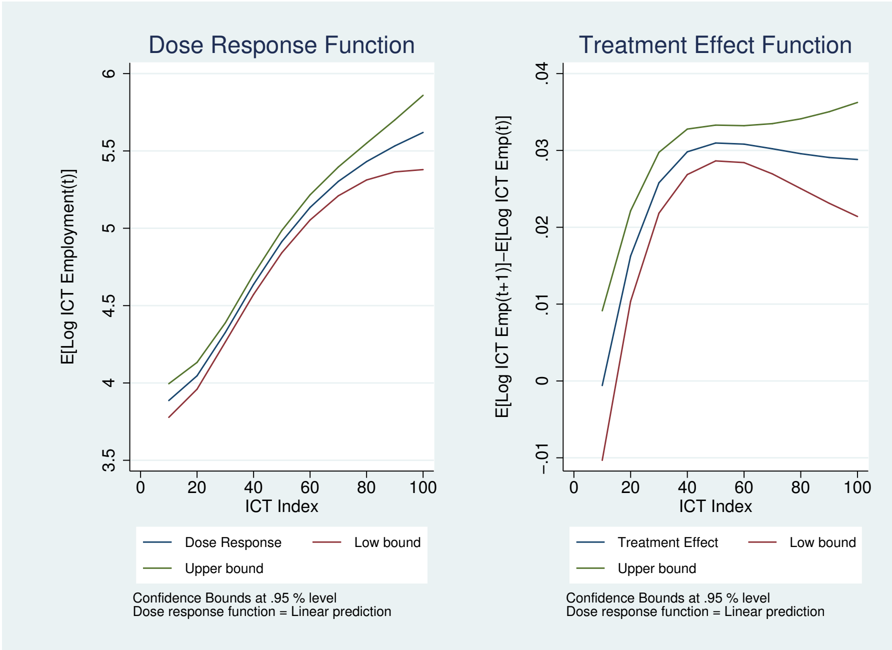
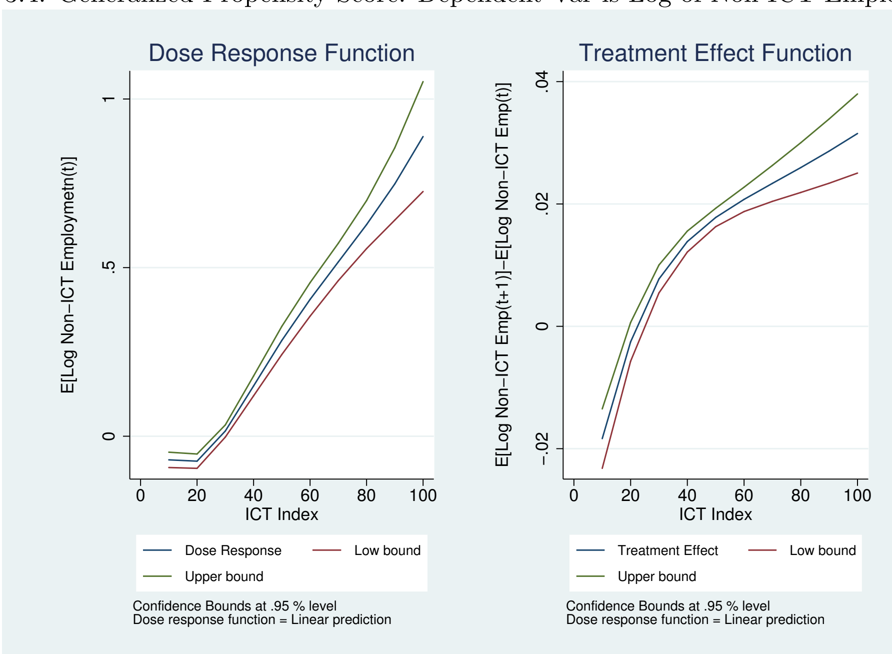


Figure 3.4: Generalized Propensity Score: Dependent Var is Log of Non-ICT Employment



Chapter 4

Information Communication Technology Skills and Employment Opportunities

4.1 Introduction

The worker-firm matching process relies heavily on the flow and quality of information.[1] Information and communication technologies (ICTs), especially the Internet, improve the matching of workers with firms by making more information accessible to both firms and workers. ICT reduces the cost of employment applications for workers and removes the geographic barrier of job search. ICTs and the Internet can also provide education and training opportunities for workers at a lower cost. As ICTs become more essential business investments, workers who have the skills that complement these technologies become more attractive on the job market.[2]

This paper studies the prevalence of ICT skills and how they affect workers' employment opportunities. Skill levels are conventionally measured by education, however innovative capacity and knowledge are not necessarily captured by educational attainment. To establish the relationship between technology use and labor market outcomes, observing the technology related skills of workers is important. The role of ICT skills in improving employment opportunities can be even more critical in emerging countries where these skills are more scarce compared to the developed world.

ICT skills and employment outcomes can be related in three ways. First, ICT skills can directly increase the probability of being employed for workers. Second, workers can learn these skills on the job. Third, workers can gain other skills and training though the Internet using their ICT skills.

There is limited evidence on the effects of ICTs on the job market outcomes of workers, mostly due to lack of micro-data. Kuhn and Skuterud (2004) and Stevenson (2009) use Current Population Survey data to analyze the effects of Internet job search on workers. Kuhn and Skuterud (2004) find that Internet job search is associated with lower unemployment durations. However this relationship is eliminated when observable

[1] Autor (2001).

[2] Additionally on the demand side, there is a well-established literature on skilled-biased technological change. Acemoglu (1998), Autor, Katz, and Krueger (1998) and Autor, Levy, and Murnane (2001) find evidence that information technologies are skill biased. Michaels, Natraj, and Van Reenen (2010) provide evidence that ICTs are skilled biased as well. ICTs are considered as skill-biased because they change the relative demand for skilled and unskilled labor. ICTs require skilled labor for maintenance and use. Therefore, adoption of these technologies increases the demand and wages for skilled labor.

variables are held constant. Stevenson (2009) analyzes on-the-job search and finds that the workers who use Internet job search methods are more likely to make an employment-to-employment transition. Empirical evidence on ICT skills and employment opportunities of workers is scarce. In an experimental study, Blanco and Boo (2010) submit fictitious curriculum vitae(CVs) to real job vacancies. The CVs that had ICT skills listed had 1 percent higher chance to get a call back controlling for other characteristics. To my knowledge, there are no studies on the relationship between ICT skills and employment in developing countries using representative micro-data. This paper aims to provide the first evidence on the prevalence of workers' ICT skills in a developing country and how these skills relate to workers' employment probability.

First, I summarize the prevalence of ICT skills over time. In the country I study, Turkey, ICT skills are not very common among the working-age population; for example only 31 percent of the people can perform a very basic function as copying and pasting in 2010. This percentage is even lower for more advanced skills; 4 percent of the people know a programming language. One important reason people lack these skills is not having access to technology. ICT skills are more prevalent among people who have home computers and Internet access. More of the working population have acquired these skills over time as computer and Internet use rates increase.

The probit regressions suggest there is a positive relationship between having ICT skills and the probability of being employed. However, these analyses have potential endogeneity problems, which can be caused by two mechanisms. First, unobserved skill bias can affect an individual's probability of being employed and the level of ICT skills. Significant education gaps between people who have ICT skills and those who do not confirm that there is a skill bias. This education gap increases by age: older people are less likely to have ICT skills, and the ones who have ICT skills are more educated compared to others in their age group. I control for this skill bias by using the difference in years of education for each individual compared to his age group. When this variable is added in the probit regressions, the coefficient of ICT skills on the probability of being employed decreases.

The second type of potential endogeneity problem is reverse causality. Workers can gain ICT skills at work; indeed 8 percent of all people who have at least one ICT skill reported that they gained these skills at work. Interactions of ICT skills and where these skills are acquired show that the significant relationship between ICT skills and employment status is only due to people who reported that they gained these skills at work. This evidence suggests that there is significant on-the-job learning and possible identification of suitable candidates for in-house training of these skills. Off-the-job skill acquisition is not correlated with higher probability of being employed in this sample. These results also support he idea that ICT skills are an important type of firm specific human capital that can be gained at work.

4.2 Data

I employ an individual and household-level data set from the Turkish Statistical Institute and the State Planning Organization of Turkey. This confidential data set includes surveys on ICT adoption and use from 2007 to 2010. The surveys are nationally representative repeated cross-sections with approximately 75,000 observations over four years. When I restrict the sample to people of working age, 16 to 65, the number of observations drops to 48,404.

The data include household adoption information such as presence of computers, the Internet and other ICT devices at home. There are individual-level questions for each member of the household. These questions provide detailed information of ICT adoption and use by the individuals, as well as purposes, locations, and frequency of ICT use. Additionally, this data set includes information on ICT skills and where people gained these ICT skills.

Individuals report the ICT skills they have among the following options:

1. Copying and transferring files/folders,

2. Using copy/paste command,

3. Using formulas in a spreadsheet,

4. Zipping files/folders,

5. Connecting and installing devices to a computer (modem, scanner, etc.)'

6. Knowing a programming language,

7. Connecting computers to networks,

8. Problem solving/trouble shooting involving computers and the Internet.

These skills are ranked based on their complexity. I have classified these skills into three groups: basic ICT skills, medium-level ICT skills, and advanced ICT skills. The most basic skills include copying and transferring files/folders and using copy/paste command. Medium skills include using formulas in a spreadsheet, zipping files/folders, and connecting devices to a computer. Advanced skills are knowing a programming language, connecting computers to networks, and problem solving involving the Internet and computers.

The next question in the survey asks where people gained these ICT skills. These variables are helpful controlling for the endogeneity of ICT skill variables. These questions are only available for 2007 and 2008.

There are six possible answers for the question, "Where/how did you gain the ICT skills you have listed?":

1. At an educational institute (school, college),
2. In a workshop/class by your own initiation (without employer's demand),
3. In a workshop/class by employer's demand or at work ,
4. Individually with the help of books and DVDs,
5. Individually with experience/trial and error,
6. With the help of your friends and family.

Table 4.1 summarizes the ratio of people who have listed ICT skills. Even very basic tasks such as copy/paste and file transfer are reported by only 30-40 percent of workers in the labor force. This shows the basic skills that may be taken for granted in the developed world are not necessarily widespread in the developing world.

According to the survey, 26 percent of Turkish households had home computer access in 2007, by 2010 this had increased to 46 percent. Likewise, households with home Internet access increased from 20 percent in 2007 to 46 percent in 2010. Panels B and C of Table 4.1 show the ratio of people who have ICT skills given home computer and home Internet access, respectively. As expected, people with access to a computer and the Internet at home have a higher probability of having more ICT skills.

Table 4.2 summarizes my measure of the rankings based on the survey questions, showing the ratio of people who have any ICT skill, any basic ICT skill, any medium ICT skill, and any advanced ICT skill. The basic skills are more common and the prevalence for all types of ICT skills are higher given home computer and Internet access. The prevalence also increases over time.

Table 4.3 summarizes where the ICT skills are acquired among the people who have any of the ICT skills. People can list more than one mechanism, so the ratios do not add up to 1. Most people said they have gained ICT skills through friends and family, trial and error, or at an educational institute. In 2007 and 2008, 8% of the people who have one or more ICT skill reported they gained the skill(s) at work or through a workshop with employer's demand.

4.3 Empirical Specification and Results

I use the following basic probit model for empirical specification:

$$Pr(\text{Employment Status}_i = 1) = \Phi(\beta_0 + \beta_1 \text{ICT Skills}_i + \delta X_i + \alpha Z_h + \lambda_t + \epsilon_i), \tag{4.1}$$

where Employment Status$_i$ is an indicator for whether individual i is employed or not, ICT Skills$_i$ is the ICT skill-level ranking of individual i, X_i includes individual controls, and Z_h includes household-level control variables. The time control that absorbs time specific shocks shared by all the individuals is λ_t.

The individual-level control variables include years of education, age, gender, residence in an urban area, and whether they think they have a foreign language barrier (English) that makes them less able to use ICTs. Race is not an important control variable for Turkey as it is a homogeneous society and the foreign immigration rate is negligible. Household-level control variables include the presence of a computer, the Internet, and other ICT devices (iPad, smart phone, scanner) at home and the number of working people in the household besides the individual.

Table 4.4 presents the probit regressions for basic ICT skills. Column 1 includes simple regressions without any individual or household-level control variables. Individual-level control variables are added in column 2. Including the household-level controls leads to a basic ICT skills coefficient of 0.32. The marginal effect of having a basic ICT skill when all other control variables are at their mean levels is 12 percent. Controlling for time and individual and household characteristics, having at least one basic ICT skills is associated with around 12 percent higher probability of being employed.

Tables 4.5 and 4.6 present similar probit analysis for medium ICT skills and advanced ICT skills respectively. The first column presents the coefficients without any control variables. Column 2 introduces the individual-level controls and column 3 introduces the household-level controls along with the time fixed effects. Having at least one medium ICT skill is associated with 11 percent higher probability of being employed when all other independent variables are at their mean values. This probability is 10 percent for people who have at least one advanced ICT skills.

4.4 Skill Bias

One concern regarding the empirical specification is skill bias. The significant relationship between employment status and ICT skills might be spurious due to unobserved skills that are correlated with both. For example, an individual with higher IQ will have a higher probability of being employed and acquiring ICT skills. To find some evidence supporting this assertion, I analyze the education gap between people who have ICT skills and people who do not have ICT skills. The education gap is the difference in average years of education between people with and without ICT skills. Additionally, younger people have a higher probability of gaining ICT skills. This can lead the unobservable bias associated with ICT skills to be different for people at different ages. To account for this, I explore how this education gap changes for people of different ages.

Table 4.7 shows the education gap between people who have basic ICT skills and the people who do not have basic ICT skills for different age groups and over time. For each age group, I calculate the difference in average years of education between people with and without ICT skills. I drop observations of people age 60-65 because there were only a couple of people with ICT skills. The difference in education between people with and without advanced ICT skills increases with age. All the differences in education within and between groups are statistically significant.

Table 4.8 shows the education gap between people who have medium ICT skills and the people who do not have medium ICT skills for different age groups and over time. Similarly, the difference in years of education between people with and without medium ICT skills increases by age. The education gap within groups decrease for the most part for younger age groups and increase for some older age groups. However, the differences for the older age groups are not statistically significant. Table 4.9 shows the education gap between people who have advanced ICT skills and the people who do not have advanced ICT skills for different age groups and over time. Here again there is a similar pattern as in the gap for medium skills.

Overall skill bias is different at different ages and over time. The skill bias is higher for older people. To control for some of the skill bias, I calculate the difference between the individual's years of education and the average years of education of his age cohort. This variable is used as a proxy for the skill bias. Tables 4.10, 4.11 and 4.12 include the skill bias proxy into the profit regressions of basic, medium and advanced ICT skills, respectively. Once this education difference variable is added in the probit regressions, the coefficients of ICT skills decrease. The marginal effect of having at least one basic ICT skill from 12 percent drops to 9 percent, the marginal effect of having at least one medium ICT skill drops from 11 percent to 8 percent and the marginal effect of having at least one advanced ICT skills drops from 10 percent to 6 percent. This evidence suggests that some of the relationship between ICT skills and employment status is due to the skill bias.

Another potential problem is reverse causality: employed people can gain ICT skills at work. Indeed, employers might require ICT training programs and workshops. I use the question about where people gained ICT skills to address this problem. In the sample, 8 percent of people indicated that they have gained ICT skills at work. This question is only available for 2007 and 2008. I drop the observations from 2009 and 2010 in this section, thus the sample size drops to 24,124 observations.

I include interaction terms between the ICT skills and where people gained ICT skills to analyze whether the relationship between skills and employment are due to certain ways in which people acquire these skills. Table 4.13 presents the employment probit regressions for years 2007 and 2008. Column 1 presents the coefficient of basic skills without any control variables, column 2 includes the individual controls and column 3 includes the household controls. Column 4 introduces the interaction terms between the basic ICT skills and how people gained the skills. The only interaction term that is significant is the one between basic ICT skills and gaining these skills at work. The level of the basic skills coefficient is insignificant as well, suggesting the positive relationship between basic skills and employment is only due to people who gained these skills at work, thus lending some support to reverse causality explanation. Table 4.14 and 4.15 presents the profit regressions using the medium ICT skills and advanced ICT skills variables, respectively. The results remain similar for medium advanced ICT skills.

These results suggest that there is on-the-job learning for ICT skills in Turkey. Off-the-job skill acquisition does not lead to higher chances of being employed. One reason for these results could be the scarcity of ICT skills in Turkey. Given that these skills are not very common, the workers who gain these skills can experience an employment-to-employment transition, such as moving to a job with higher wages and promotion. However, this type of employment-to-employment transition is not captured in the data set. Other labor market outcomes that may be affected by having ICT skills, such as wages, occupations, and job descriptions, are not observed. Further research would be needed to analyze the effects on other labor market outcomes that could be affected by having ICT skills.

4.5 Conclusion

This study aims to provide the first evidence on the prevalence of ICT skills and how these skills might affect the probability of being employed in a developing country. I use a confidential individual-level and nationally representative data set provided by the Turkish Statistical Institute. Data show the adoption and use of computers and the Internet have increased rapidly between 2007 and 2010. ICT skills also became more widespread over time and among people who have home computer and Internet access.

Having at least one basic, medium, or advanced ICT skill is associated with a higher probability of being employed. There are two types of endogeneity problems in the probit analysis: the skill bias and reverse causality. There is evidence for the skill bias in the data as there is a significant education gap between people who have ICT skills and people who do not have ICT skills. This education gap is larger for older people. To proxy for skill I use the difference in an individual's years of education compared to his age cohort. Controlling for the education gap decreases the magnitude of ICT skill coefficients.

There is also evidence for potential reverse causality, as 8 percent of all people who have at least one ICT skill reported that they gained these skills at work. The significant relationship between ICT skills and employment probability is only due to people who gained these skills at work. Controlling for observable characteristics, a proxy for ability, and where the ICT skills are gained, there is no conclusive evidence on the causal direction from ICT skills to employment. These data provide evidence that there is significant on-the-job learning for the ICT skills in Turkey. Results also support that ICT skills can be part of firm-sspecific human capital. Off-the-job ICT skill acquisition is not associated with higher probabilities of being employed.

4.6 Tables

Table 4.1: ICT Skills

A. All Individuals

	2007	2008	2009	2010
File/folder copy and transfer	0.26	0.33	0.35	0.37
Using copy/paste command	0.22	0.28	0.30	0.31
Using formulas in a spreadsheet	0.11	0.13	0.15	0.17
Zipping files/folders	0.14	0.17	0.18	0.20
Connecting and installing devices to computer	0.11	0.13	0.15	0.17
Knowing a programming language	0.03	0.03	0.03	0.03
Connecting computers to networks	0.06	0.08	0.09	0.10
Problem solving/trouble shooting about computers	0.09	0.11	0.12	0.13
B. Individuals with home computer access				
File/folder copy and transfer	0.53	0.57	0.58	0.58
Using copy/paste command	0.49	0.50	0.51	0.50
Using formulas in a spreadsheet	0.25	0.26	0.28	0.29
Zipping files/folders	0.33	0.34	0.34	0.34
Connecting and installing devices to computer	0.27	0.28	0.28	0.29
Knowing a programming language	0.08	0.08	0.07	0.07
Connecting computers to networks	0.28	0.31	0.29	0.34
Problem solving/trouble shooting about computers	0.18	0.17	0.17	0.18
C. Individuals with home Internet access				
File/folder copy and transfer	0.54	0.56	0.58	0.59
Using copy/paste command	0.51	0.52	0.51	0.52
Using formulas in a spreadsheet	0.28	0.28	0.28	0.28
Zipping files/folders	0.34	0.33	0.36	0.37
Connecting and installing devices to computer	0.30	0.30	0.29	0.29
Knowing a programming language	0.08	0.08	0.06	0.06
Connecting computers to networks	0.25	0.26	0.24	0.25
Problem solving/trouble shooting about computers	0.20	0.19	0.19	0.18

Table 4.2: ICT Skills

A. All Individuals

	2007	2008	2009	2010
Any one of the ICT skills	0.32	0.38	0.42	0.44
Any one of the basic ICT skills	0.27	0.34	0.36	0.38
Any one of the medium ICT skills	0.17	0.21	0.23	0.24
Any of the the advanced ICT skills	0.11	0.14	0.15	0.17

B. Individuals with home computer access

Any one of the ICT skills	0.64	0.67	0.68	0.69
Any one of the basic ICT skills	0.56	0.57	0.59	0.60
Any one of the medium ICT skills	0.40	0.42	0.43	0.45
Any one of the advanced ICT skills	0.25	0.26	0.28	0.30

C. Individuals with home Internet access

Any one of the ICT skills	0.66	0.67	0.71	0.72
Any one of the basic ICT skills	0.60	0.60	0.62	0.61
Any one of the medium ICT skills	0.40	0.43	0.44	0.44
Any one of the advanced ICT skills	0.28	0.29	0.31	0.32

Table 4.3: Where the ICT Skills are gained

Ratios among people who have any of ICT skills

	2007	2008
At an institute (School, college)	0.25	0.25
In a workshop/class with your own initiation (without employer's demand)	0.15	0.15
In a workshop/class with employer's demand or at work	0.08	0.08
On your own with the help of books and DVDs	0.07	0.07
On your own with experience/trial and error	0.71	0.68
With help from your friends and family	0.47	0.55

Table 4.4: Probit for Basic ICT Skills

Dependent Variable: Employment Status

	(1) no controls	(2) individual controls	(3) household controls
Basic ICT skills	0.4410***	0.2700***	0.3246***
	(0.0121)	(0.0163)	(0.0174)
Years education		0.0607***	0.0636***
		(0.0017)	(0.0018)
Language Barrier		-0.0384	-0.0185
		(0.0533)	(0.0535)
Age		0.0045***	0.0046***
		(0.0005)	(0.0005)
Female		-0.0516***	-0.0522***
		(0.0117)	(0.0117)
Urban		-0.4405***	-0.4301***
		(0.0133)	(0.0137)
Household computer			-0.0533
			(0.0341)
Household other devices			0.0514***
			(0.0171)
Household Internet			-0.0948***
			(0.0166)
Number of other people working in the household			-0.0067
			(0.0061)
Year 2007		0.1075***	0.0667***
		(0.0168)	(0.0183)
Year 2008		0.0812***	0.0610***
		(0.0163)	(0.0165)
Year 2009		-0.0007	-0.0154
		(0.0166)	(0.0167)
Observations	48,404	48,404	48,404

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.5: Probit for Medium ICT Skills

Dependent Variable: Employment Status

	(1) no controls	(2) individual controls	(3) household controls
Medium skills	0.4575***	0.2312***	0.2932***
	(0.0139)	(0.0172)	(0.0186)
Years education		0.0655***	0.0681***
		(0.0017)	(0.0018)
Language Barrier		0.0011	0.0267
		(0.0532)	(0.0535)
Age		0.0034***	0.0033***
		(0.0005)	(0.0005)
Female		-0.0502***	-0.0506***
		(0.0117)	(0.0117)
Urban		-0.4325***	-0.4240***
		(0.0133)	(0.0137)
Household computer			-0.0380
			(0.0341)
Household other devices			0.0489***
			(0.0172)
Household Internet			-0.0886***
			(0.0166)
Number of other people working in the household			-0.0088
			(0.0061)
Year 2007		0.0990***	0.0607***
		(0.0167)	(0.0183)
Year 2008		0.0814***	0.0639***
		(0.0163)	(0.0165)
Year 2009		0.0026	-0.0102
		(0.0166)	(0.0166)
Observations	48,404	48,404	48,404

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.6: Probit for Advanced ICT Skills

Dependent Variable: Employment Status

	(1) no controls	(2) individual controls	(3) household controls
Advanced ICT skills	0.4440***	0.2230***	0.2731***
	(0.0164)	(0.0185)	(0.0197)
Years education		0.0694***	0.0723***
		(0.0016)	(0.0017)
Language barrier		0.0289	0.0576
		(0.0531)	(0.0534)
Age		0.0029***	0.0027***
		(0.0005)	(0.0005)
Female		-0.0495***	-0.0496***
		(0.0117)	(0.0117)
Urban		-0.4311***	-0.4242***
		(0.0133)	(0.0137)
Household computer			-0.0224
			(0.0340)
Household other devices			0.0462***
			(0.0172)
Household Internet			-0.0860***
			(0.0166)
Number of other people working in the household			-0.0096
			(0.0061)
Year 2007		0.0972***	0.0614***
		(0.0167)	(0.0183)
Year 2008		0.0790***	0.0629***
		(0.0163)	(0.0165)
Year 2009		0.0051	-0.0060
		(0.0166)	(0.0166)
Observations	48,404	48,404	48,404

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.7: Education gap between people with and without **basic ICT skills**

	Age Group								
Year	16-20	21-25	26-30	31-35	36-40	41-45	46-50	51-55	56-60
2007	3.54	5.54	5.66	5.54	5.90	5.82	6.34	7.36	8.25
2008	2.91	4.83	5.44	5.59	5.93	5.46	6.49	6.77	7.83
2009	3.21	5.75	5.79	6.11	5.86	6.09	6.63	7.41	8.48
2010	2.84	5.25	5.79	5.47	6.29	6.18	6.59	7.50	8.03

Table 4.8: Education gap between people with and without **medium ICT skills**

	Age Group								
Year	16-20	21-25	26-30	31-35	36-40	41-45	46-50	51-55	56-60
2007	2.67	5.38	5.69	6.04	6.23	6.73	7.06	8.02	8.68
2008	2.42	4.64	5.84	6.15	6.57	6.25	7.05	7.58	8.95
2009	2.33	5.35	6.23	6.49	6.38	6.37	6.98	8.14	8.79
2010	2.33	5.06	6.06	5.86	6.78	7.32	7.06	8.17	8.25

Table 4.9: Education gap between people with and without **advanced ICT skills**

	Age Group								
Year	16-20	21-25	26-30	31-35	36-40	41-45	46-50	51-55	56-60
2007	2.15	4.67	5.48	5.76	5.65	6.79	8.56	9.66	9.66
2008	2.05	3.90	5.23	5.50	6.01	7.04	7.05	8.84	8.84
2009	1.90	4.41	5.16	5.87	5.97	5.98	7.27	8.63	8.63
2010	1.99	3.90	5.03	5.22	6.12	6.62	7.09	7.17	7.17

Table 4.10: Probit for Basic ICT Skills

Dependent Variable: Employment Status			
	(1)	(2)	(3)
	no controls	individual controls	households controls
Basic skills	0.4410***	0.2110***	0.2436***
	(0.0121)	(0.0163)	(0.0174)
Years education		0.0501***	0.0525***
		(0.0017)	(0.0018)
Difference of education from age group		0.0211***	0.0252***
		(0.0018)	(0.0019)
Language Barrier		-0.0392	-0.0189
		(0.0533)	(0.0535)
Age		0.0044***	0.0045***
		(0.0005)	(0.0005)
Female		-0.0520***	-0.0521***
		(0.0117)	(0.0117)
Urban		-0.4408***	-0.4310***
		(0.0133)	(0.0137)
Household computer			0.0533
			(0.0341)
Household other devices			0.0521***
			(0.0171)
Household Internet			0.0923***
			(0.0166)
Number of other people working in the household			-0.0067
			(0.0061)
Observations	48,404	48,404	48,404
Year Controls	No	Yes	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.11: Probit for Medium ICT Skills

Dependent Variable: Employment Status			
	(1)	(2)	(3)
	no controls	individual controls	household controls
Medium skills	0.4575***	0.1972***	0.2574***
	(0.0139)	(0.0172)	(0.0186)
Years education		0.0655***	0.0681***
		(0.0017)	(0.0018)
Difference of education from age group		0.0227***	0.0258***
		(0.0018)	(0.0019)
Language Barrier		0.0012	0.0264
		(0.0532)	(0.0535)
Age		0.0033***	0.0032***
		(0.0005)	(0.0005)
Female		-0.0504***	-0.0503***
		(0.0117)	(0.0117)
Urban		-0.4343***	-0.4262***
		(0.0133)	(0.0137)
Household computer			0.0380
			(0.0341)
Household other devices			0.0485***
			(0.0172)
Household Internet			0.0872***
			(0.0166)
Number of other people working in the household			-0.0088
			(0.0061)
Observations	48,404	48,404	48,404
Year Controls	No	Yes	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.12: Probit for Advanced ICT Skills

Dependent Variable: Employment Status

	(1) no controls	(2) individual controls	(3) household controls
Advanced skills	0.4440***	0.1782***	0.1963***
	(0.0164)	(0.0185)	(0.0197)
Years education		0.0521***	0.0523***
		(0.0016)	(0.0017)
Difference of education from age group		0.0239***	0.0274***
		(0.0018)	(0.0019)
Language barrier		0.0281	0.0569
		(0.0531)	(0.0534)
Age		0.0028***	0.0027***
		(0.0005)	(0.0005)
Female		-0.0487***	-0.0492***
		(0.0117)	(0.0117)
Urban		-0.4324***	-0.4275***
		(0.0133)	(0.0137)
Household computer			0.0233
			(0.0340)
Household other devices			0.0461***
			(0.0172)
Household Internet			0.0852***
			(0.0166)
Number of other people working in the household			-0.0095
			(0.0061)
Observations	48,404	48,404	48,404
Year Controls	No	Yes	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.13: Basic ICT Skills Interactions

Dependent Variable: Employment Status				
	(1)	(2)	(3)	(4)
Basic skills	0.4163***	0.2162***	0.2361***	0.0093
	(0.0176)	(0.0258)	(0.0276)	(0.0476)
Years education		0.0507***	0.0562***	0.0599***
		(0.0019)	(0.0020)	(0.0020)
Education Difference		0.02777***	0.0259***	0.0225***
		(0.0019)	(0.0020)	(0.0021)
Language Barrier		-0.0948	-0.0753	-0.1356**
		(0.0578)	(0.0582)	(0.0590)
Age		0.0491***	0.0519***	0.0497***
		(0.0018)	(0.0019)	(0.0019)
Female		-1.2641***	-1.3099***	-1.3089***
		(0.0184)	(0.0190)	(0.0192)
Urban		-0.4753***	-0.4330***	-0.4416***
		(0.0197)	(0.0203)	(0.0203)
Household computer			0.2015***	0.1185**
			(0.0533)	(0.0534)
Household other devices			0.0591***	0.0453**
			(0.0222)	(0.0223)
Household Internet			0.1432***	0.1617***
			(0.0341)	(0.0303)
Number of other people working in the household			0.1200***	0.1207***
			(0.0090)	(0.0090)
Skills Obtained				
Basic x Institute				-0.0218
				(0.0371)
Basic x Courses				0.0201
				(0.0463)
Basic x Work				0.4378***
				(0.0645)
Basic x Books				-0.0870
				(0.0617)
Basic x Experience				0.0489
				(0.0364)
Basic x Friend				-0.0404
				(0.0340)
Observations	24,124	24,124	24,124	24,124
Year Control	No	Yes	Yes	Yes

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4.14: Medium ICT Skills Interactions

Dependent Variable: Employment Status				
	(1)	(2)	(3)	(4)
Medium skills	0.4343***	0.1879***	0.2068***	0.0600
	(0.0205)	(0.0272)	(0.0293)	(0.0564)
Years education		0.05032***	0.0519***	0.0513***
		(0.0019)	(0.0019)	(0.0020)
Education Difference		0.0251***	0.0229***	0.0239***
		(0.0019)	(0.0020)	(0.0020)
Language Barrier		-0.0653	-0.0440	-0.1334**
		(0.0575)	(0.0580)	(0.0589)
Age		0.0476***	0.0503***	0.0519***
		(0.0018)	(0.0018)	(0.0019)
Female		-1.2695***	-1.3161***	-1.3037***
		(0.0184)	(0.0189)	(0.0192)
Urban		-0.4680***	-0.4272***	-0.4417***
		(0.0196)	(0.0202)	(0.0203)
Household computer			0.2160***	0.1371**
			(0.0534)	(0.0537)
Household other devices			0.0594***	0.0502**
			(0.0222)	(0.0223)
Household Internet			0.1506***	0.2049***
			(0.0275)	(0.0281)
Number of other people working in the household			0.1189***	0.1223***
			(0.0090)	(0.0090)
Skills Obtained				
Medium x Institute				-0.0283
				(0.0433)
Medium x Courses				0.0214
				(0.0530)
Medium x Work				0.4106***
				(0.0722)
Medium x Books				-0.0650
				(0.0667)
Medium x Experience				-0.0098
				(0.0475)
Medium x Friend				-0.0669
				(0.0424)
Observations	24,124	24,124	24,124	24,124
Year Control	No	Yes	Yes	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.15: Advanced ICT Skills Interactions

Dependent Variable: Employment Status				
	(1)	(2)	(3)	(4)
Advanced skills	0.4406***	0.1282***	0.1373***	-0.0086
	(0.0243)	(0.0294)	(0.0294)	(0.0656)
Years education		0.0502***	0.0502***	0.0520***
		(0.0019)	(0.0019)	(0.0020)
Education Difference		0.0241***	0.0241***	0.0233***
		(0.0019)	(0.0018)	(0.0019)
Language Barrier		-0.0374	-0.0418	-0.1341**
		(0.0573)	(0.0573)	(0.0586)
Age		0.0467***	0.0485***	0.0528***
		(0.0018)	(0.0018)	(0.0019)
Female		-1.2695***	-1.2636***	-1.3011***
		(0.0184)	(0.0187)	(0.0191)
Urban		-0.4649***	-0.4623***	-0.4413***
		(0.0196)	(0.0202)	(0.0203)
Household computer			0.2294***	0.1353**
			(0.0531)	(0.0537)
Household other devices			0.0739***	0.0521**
			(0.0222)	(0.0223)
Household Internet			0.1483***	0.2039***
			(0.0274)	(0.0281)
Number of other people working in the household			0.1123***	0.1211***
			(0.0089)	(0.0090)
Skills Obtained				
Advanced x Institute				-0.0127
				(0.0529)
Advanced x Courses				0.0210
				(0.0648)
Advanced x Work				0.4734***
				(0.0879)
Advanced x Books				-0.1094
				(0.0769)
Advanced x Experience				0.0254
				(0.0588)
Advanced x Friend				-0.0672
				(0.0516)
Observations	24,124	24,124	24,124	24,124
Year Control	No	Yes	Yes	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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