Firm-Level Evidence of the Effects of IT Use on Employment and Labor Wages*

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Abstract

This study analyzes the adoption and use of information technology (IT) by firms and their effects on employment and labor wages. Despite the prevalent role of IT in todays economy, the question on whether and how IT contributes to employment and wages has not been addressed in the IS literature. We use IT complementarities, skilled-biased technical change, and lagged-effects of IT theories to derive predictions on the effects of IT use on IT labor and on non-IT labor, respectively. We hypothesize that IT use has direct positive effect on IT labor, and an indirect positive effect on non-IT labor, effects that materialize through changes in net output and productivity (value-added per employee). We examine data from Turkey that include detailed information on IT infrastructure, IT applications, and software use, e-commerce and IT outsourcing. Using the generalized propensity score matching and instrumental variables methods to address concerns of endogeneity, our results show positive effects of IT on employment and wages at the firm level. This effect is largely due to an increase in IT jobs in the short-run, implying that IT use has direct immediate effects on IT employment. However, the effects on non-IT employment become significant only with lagged (one- and two-year) effects of IT use. This is because the effects of IT on non-IT employment take time to realize through increases in output and productivity. We also find similar lagged-effects of IT on output and productivity. Theoretical and practical implications on the effects of IT on employment and labor wages are discussed along with implications for public policy.

Keywords: Information technologies, employment, wages, IT labor, non-IT labor, skilled-biased technological change

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1 Introduction

There is an extensive literature on the effects of IT and economic performance (please see Dedrick, Gurbaxani and Kreamer 2003 for a detailed review). The majority of these papers focus on the effects of IT investments, IT capital, and IT spending on firm productivity (e.g., Lichtenberg 1995; Brynjolfsson and Hitt 1996; Greenan et al. 2001; Brynjolfsson and Hitt 2003). These papers find significant returns of IT on productivity and output, especially for the firms that IT investments co-exist with complementary firm resources. Moreover, there are many aggregate studies on how a stronger local IT infrastructure is associated with higher average employment and higher average wages (e.g., Forman et al. 2012, Crandall et al. 2007, Kolko 2010, Atasoy 2012). However, despite the broader effects of IT in todays economy, the question on whether and how firm-level IT use contributes to employment and labor wages has not been adequately addressed in the IS literature. In this study, we address this gap using a unique firm-level data source from Turkey.[1]

We analyze how IT use affects firm demand for IT labor and non-IT labor along with productivity and output. In our sample, IT labor includes IT experts and IT users. In the data, IT experts are defined as employees whose main job is IT and who are capable of designing, installing, operating, developing, supporting, maintaining, repairing, and evaluating IT systems. Computer programmers, software engineers, and systems analysts are some examples of occupations in this category. IT users are employees that majority of their job involves IT use on a daily basis and who are advanced users of general purpose and sector specific software. Data analysts and database users are some examples of IT users. Non-IT labor is calculated by subtracting IT labor from the total number of employees for each firm. We use value-added per employee as a measure of firm productivity and net output as a measure of firm output level. [2]

The effects of IT use on employment and wages are justified by theories of resource com-

[1] This data can be accessed through Turkish Statistical Institute Data Research Center with an application.
[2] Value-added is calculated as follows: Value-added=output+changes in stcoks+total investment+rent revenue-total costs-taxes.

plementarities (e.g., Milgrom and Roberts 1990, Bresnahan and Trajtenberg 1995), skilled biased technological change (SBTC) (e.g., Acemoglu 1998, Autor et al 2003, Breshanan et al 2003, and lagged-effects of IT (Brynjolfsson and Hitt 2003, Peffers and Dos Santos 1996, Armstrong and Sambamurthy 1999).

Resource complementarity theory posits that when resources, such as IT assets, have complementarities, their potential for value is higher. The basic idea behind the SBTC model is that IT complements skilled labor more compared to unskilled labor. Therefore, use of IT increases demand and wages for skilled labor. Integrating these theories, we derive hypotheses for the relationship between IT use with skilled IT-labor and with non-IT labor. We theorize a direct complementarity between IT and IT-labor. Therefore, we expect direct positive effects of IT use on IT labor. However, there is no direct complementarity between IT and non-IT labor (or we cannot infer on the nature of complementarily a priori) to predict that IT would affect the demand for non-IT labor through indirect channels, such as increased output that would correspond to higher labor demand. Also integrating the literature on the lagged-effects of IT on output and productivity, we hypothesize that long-term contributions of IT use on non-IT labor should exceed short-term contributions.

We find that IT use increases IT-labor demand in the short run, albeit this effect decreases over time (during the two-year period). However, lagged (one- year and two-year) IT use has significant positive effects on non-IT employment with an increasing effect over time. We find similar effects of IT use on productivity and output. These results imply that IT use has a direct immediate impact on IT labor, as hypothesized. However, IT use does not increase non-IT labor demand right away, but it requires some time for IT use to materialize its effects on non-IT labor demand through increases in output. There are similar lagged-effects of IT use on firm expansion that increases the overall demand for labor.[3]

Our paper makes two major contributions. First, it is one of the first studies to analyze

[3]There is an endogeneity problem in analyzing the relationship between IT use and employment/wages due to reverse causality. We address this endogeneity concern using firm fixed effects models and conducting various analyses to make sure our main results remain similar under different assumptions. We check the robustness of the results with generalized propensity score matching and instrumental variable methods.

the effects of firm-level IT use on labor demand by differentiating between IT and non-IT labor. We theorize distinct effects of IT use on IT and non-IT labor using complementary resources, skilled-biased technological change, and lagged-effects of IT theories. Second, while most prior work has used data from large firms such as Fortune 1000 (Tambe and Hitt 2012), IT use of large firms is significantly different than small and medium firms. However, there is not much evidence whether findings from large firms would equally apply to medium or small firms. We use a nationally representative dataset that includes many small and medium firms and thus making our results relevant for public policy implications.

2 Theoretical Development

In recent studies, IT labor has been used as a measure of IT investments (instead of IT capital). For example, Tambe and Hitt (2012) found that returns on IT investment are lower in small and mid-size firms, but they materialize more slowly in large firms (using IT-labor as a measure of IT investment). In another study that estimated the effects of IT labor on productivity at the industry level, Han, Nault and Lee (2012) further differentiated between IT labor and non-IT labor and found that IT labor contributes to productivity (both IT capital and IT outsourcing) in IT-intensive industries, whereas these effects are smaller in less IT-intensive industries. These studies provide important insights about the contribution of IT capital and IT labor on productivity and output. However, there are not many studies addressing how IT affects firm employment for IT-labor and non-IT labor.

We develop a new theory by integrating the literature on IT complementarities with the skilled biased technological change (SBTC) theory and the lagged-effects of IT literature to theorize the effects of IT on labor demand and employment. Resource complementary and SBTC theories suggest that IT and IT labor are complementary, thus IT use would have a direct positive impact on IT labor. There is no direct relationship between IT use and non-IT labor. We expect IT use to affect non-IT labor through changes in output and productivity.

Here we utilize the literature of lagged-effect of IT. Since IT has larger impacts on output and productivity over time, we expect more positive impacts on non-IT labor over time as well.

The theory of complementary resources theorizes that various firm assets, skills, and resources that are mutually complementary and help co-create business value. These complementary resources make each other more valuable (Milgrom et al. 1991). This view is used to explain several performance variations and competitive advantage across firms and industries (Barney 1991, Mishra and Agarwal 2010). Zhu (2004) used complementarities between IT and e-commerce resources to assess the value of electronic business. The IT complementarities view was also used to explain firm behavior within industry-level technological change process (King et al. 2003). We use this framework in the context of relationships between IT, IT-labor and non-IT labor. IT-labor is sum of IT experts and IT users. IT experts are the employees who are capable of designing, maintaining, and repairing IT systems (e.g., computer programmers, software engineers). IT users are employees who are advanced users of software and IT applications and majority of their time is involves IT use (e.g., data analysts, database users). Non-IT labor is calculated by subtracting IT labor from total number of employees. IT employment (total number of IT labor at the firm) is directly generated by the level of IT intensity in the firm because these are employees specifically hired for designing, maintain and using IT systems. Thus, these two resources will have a complementary relationship and we expect them to create more value when they interact together. Non-IT employment (total number of non-IT labor at the firm) is not directly attached to IT level at the firm. Therefore, we cannot predict the complementarity or substitutability between IT use and non-IT labor.

Related to the more general resource complementarity theory, skilled-biased technical change theory (SBTC) specifically focuses on the relationship between IT and labor and the complementarities between them. This line of economics research is motivated by the observation that demand for skilled labor increased dramatically over the last three decades in the United States.

We adopt the basic SBTC model (Krusell et al. 2000) where the production function is Cobb-Douglas over capital and constant elasticity of substitution function of u_t, s_t and IT_t,

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

where μ and λ are the income shares, σ and ρ are the elasticity of substitution between unskilled labor, IT, and skilled labor. (σ and $\rho < 1$). The elasticity of substitution between IT (or skilled labor) and unskilled labor is $1/(1-\sigma)$, and the elasticity of substitution between IT and skilled labor is $1/(1-\rho)$. IT-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:

$$ln(\frac{w_s}{w_u}) \simeq \lambda\frac{\sigma-\rho}{\rho}ln(\frac{IT}{s})^{\rho} + (1-\sigma)ln(\frac{u}{s}) \tag{2}$$

If $\sigma > \rho$, this means the elasticity of substitution between IT and skilled labor is below the elasticity of substitution between IT and unskilled labor. This implies that IT and skilled labor are complements. Thus, the relative demand and wages for skilled labor will increase with an increase in IT investment. As the difference between σ and ρ increases, and as there are more complementarities between IT and skilled labor compared to IT and unskilled labor, the positive effect of IT on skilled labor wages also increases. This model predicts that as IT level increases, relative wages and demand for skilled labor increases. Also, as the complementary relationship is higher between IT and skilled labor, there is a higher positive impact of IT on demand and wages for skilled labor. If this hypothesis is true, higher levels of IT use will have a positive effect on relative wages and employment of skilled labor. Previous studies showed that IT investments increase the demand for skilled labor. Acemoglu (1998), Autor, Katz and Kruger (1998), Autor, Levy and Murane (2001) and

Bresnahan et al. (2002) found evidence that the increase in skilled labor wages can be explained by increase in computerization. Autor, Levy and Murane (2003) classified labor tasks as routine versus non-routine and cognitive versus non-cognitive instead of skilled versus unskilled labor. They found that within industries and occupations, computerization is related to lower demand for routine labor tasks and higher demand for non-routine cognitive labor tasks. Michaels, Natrah and Van Reenen (2010) analyzes similar question using data fro OECD countries. Bresnahan, Brynjolfsson and Hitt (2002) analyzed the effects of IT and workplace organization on skilled labor. They used complementarities between IT, workplace organization, and product innovation as drivers of SBTC. They found that the complementarities between these three factors lead to increased demand and wages for skilled labor. These studies focused on the role of IT capital and investment in shaping firm's skilled labor demand. Our study uses basic predictions of the SBTC model and focus on the distinction between IT-labor and non-IT labor instead of skilled and unskilled labor. We assume there is a similar complementary relationship between IT use and IT labor. Higher levels of IT adoption and use would lead to higher demand for IT labor for IT use.

There are two major mechanisms through which IT can affect the demand for labor at the firm level. First, IT can directly change the demand for labor. Second, IT can indirectly affect the labor demand through other mechanisms that changes firm size and productivity. Based on the predictions of the resource complementarities and SBTC theories, we expect that IT use have a direct effect on IT labor. Since IT use and IT labor have direct resource complementarities, higher levels of IT use would correspond to higher levels of IT employment. We also expect IT use to have a positive effect on wages of IT-labor.[4]However, we still expect to see a positive impact on average wages, since higher IT use would increase wages for IT-labor and not change wages for non-IT labor. We therefore propose,

H1a: IT use has a direct positive effect on IT-employment.

H1b: IT use has a direct positive effect on wages.

[4]In this study, we cannot distinguish between IT labor wages and non-IT labor wages in our sample.

We cannot predict if there is a complementary (or substitutable) relationship between IT and non-IT labor. Non-IT labor constitutes of employees of various skill levels and roles. Additionally, non-IT employment is not directly generated by the intensity of IT. However, IT can indirectly change the demand and wages for labor through other channels, such as increases in productivity and output. There is an established positive link between IT and output, and between IT and productivity. Additionally, output and productivity contributions of IT are larger over the long-term (Peffers and Dos Santos 1996, Devaraj and Kohli 2000, Brynjolfsson and Hitt 2003). There are several theoretical reasons for IT effects to materialize over time. The benefits of IT are accompanied by large and time-consuming investments in complementary inputs and investments (Brynjolfsson, Hitt and Yang 2002, Brynjolfsson and Hitt 2003). These complementary changes take time leading larger output benefits of IT over the years.

On the other hand, it takes time for employees to learn new technologies (Armstrong and Sambamurthy 1999, Singh et al. 2012). Improvements from innovations follow a learning-curve where contributions increase with an increased experience in the new technology (Reis 1991, Peffers and Dos Santos 1996). Complementary changes and learning-curve theories imply that the long-term contribution of IT on output and productivity should be higher than the short-term contribution. We expect IT use to affect non-IT labor demand through changes in output. As firm size increases, employment for non-IT labor (which is the majority of a firms labor force) would increase. We expect to see a higher impact on wages thorough increases in productivity. As labor productivity increases, the price for labor would increase as well. Since lagged-IT effects on output and productivity are larger, we predict similar larger lagged-effects of IT on non-IT labor and wages. Therefore, we propose:

H2a: Long-term contributions of IT use on non-IT employment should exceed short-term contributions.

H2b: Long-term contributions of IT use on wages should exceed short-term contributions.

We also analyze the effects on output and productivity as we predict them to be drivers for IT impacts on non-IT employment. As discussed above, there are larger lagged-effects on IT on productivity and output. Complementary changes and learning-curve theories suggest that long-run benefits of IT are larger that short-run benefits. Theory and evidence support the lagged-effects of IT for both contributions to output and productivity (Peffers and Dos Santos 1996, Devaraj and Kohli 2000, Brynjolfsson, Hitt and Yang 2002, Brynjolfsson and Hitt 2003). Therefore we propose:

H3a: Long-term contributions of IT use on output should exceed short-term contributions.

H3b: Long-term contributions of IT use on productivity should exceed short-term contributions.

3 Measuring the Firm IT level of Use

The Turkish Statistical Institute and the State Planning Organization of Turkey conducted IT adoption and use surveys from 2007-2010. These survey data include detailed questions about how much and for what purposes IT is used within firms. They are nationally representative in each year. We matched IT 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 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.[5]. The IT 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 both years. Matching IT, business, and trade datasets results in a dataset of 5,570 observations over 2007 and 2008. We also use a four-year panel that does not include the full set of control variables for some part of the analysis. Here, we use the balanced panel of 454 firms over four years with a total of 1,816 observations.

[5]2011 IT use survey and 2009 business statistics survey will be added in December 2012

There are many IT 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; thus, we summarize this information into two different measures: the IT index, and the advanced Internet use indicator. The first variable is an overall index that summarizes IT adoption, use and skill indicators, while the second variable concentrates on the intensity of IT use.

3.0.1 IT Index

The IT index is a weighted average of IT adoption, use, and skill measures. This can be interpreted as an overall measure of IT at the firm. IT adoption indicators include presence of computers and the Internet as well as the speed level of the Internet connection (ISDN, ADSL, cable, or mobile). IT use indicators are using technologies for the following purposes: enterprise resource planning, supply chain management, customer relationship management, e-commerce, e-government, e-learning, e-banking, purchasing, extranet, customer support. Finally, the IT skill indicators are measures of employees knowledge about these technologies: the share of employees who use the Internet, the share of employees with IT training, and the availability of IT education for employees. First, we calculate IT adoption, IT use, and skill indices weighing each indicator equally within the groups. Then we combine these three indices into a single IT Index. We weigh the three indicators based on the International Telecommunication Societys IT Development Index weights (International Telecommunications Union Report 2009). According to this index, IT adoption is weighted by 40 percent, IT use is weighted by 40 percent, and IT skill is weighted by 20 percent. The IT index is between 0 and 1, with 0 meaning no ITs in effect and 1 meaning full use of IT within the firms. We use different weights in order to check for robustness. The results are robust to different weights.

3.0.2 Advanced Internet Use

The second measure of IT concentrates on advanced Internet applications. The advanced Internet use indicator shows whether firms use at least 3 of the following IT applications:

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

These applications are known to affect firm change and inter-establishment communication (Forman, Goldfarb and Greenstein 2012). The empirical results are robust to using different combinations of these internet applications. These advanced Internet use indicators are highly correlated with each other. We conduct Principal Component Factoring method in order to explain the underlying patterns in these highly correlated variables. Based on the principal factor analysis the percentage of the total variance explained by each variable is almost equal. Thus, using different combinations do not change the results significantly.

3.1 Summary Statistics

Table 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,

Table 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

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 2 presents the summary statistics for IT variables. The IT Index and advanced Internet use are variables that are calculated in order to measure the IT levels within the firms. The variables represent the share of firms using each application. The percentage of firms with computers is 96%, while 83% have broadband connections. The other summary statistics are the average ratio of firms using listed IT applications. The share of firms engage in e-commerce is 23% and 62% of firms use IT for marketing purposes. 42% of firms use IT for training and educational purposes. Other commonly used applications are online banking, online transactions and e-government.

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4 Empirical Specification and Results

4.1 A firm fixed effects model of ITs and Employment

We use the following basic model for empirical specification:

$$\text{Log(employment)}_{it} = \beta_0 + \beta_1 \text{IT Index}_{it} + \delta X_{it} + \alpha_i + \lambda_t + \epsilon_{it} \tag{3}$$

where $\text{Log(employment)}_{it}$ is the log of employment in firm i at time t, IT Index_{it} is the IT 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 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 effects 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

Table 2: IT Summary Statistics

IT Adoption and Use Statistics

	Mean	Standard Deviation
IT 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: OLS and Fixed Effects

Dependent Variable: Log employment

	OLS	OLS full controls	Fixed effects	Fixed effects full controls
IT 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.

of the IT Index suggests that employment increases by 3.5% within the firms when their IT index moves from 0 to 1. In the firm fixed effects regressions, the coefficient drops to 0.4%. Table 4 presents OLS and fixed effects results where the dependent variable is log of wages per employee in each firm. A higher IT Index is also associated with higher average wages. Again, the magnitudes of the coefficients are smaller when we control for firm heterogeneity.

Table 4 presents OLS and fixed effects results where the dependent variable is log of wages per employee in each firm. A higher IT Index is also associated with higher average wages. Again, the magnitudes of the coefficients are smaller when we control for firm heterogeneity.

4.2 IT employment Vs Non-IT employment

Next, we analyze the effects of IT use on different types of labor. There are two categories listed in the data set for IT-related employment: IT experts and IT users. IT experts are the employees who design and maintain computer networks and databases. IT users are

Table 4: OLS and Fixed Effects

Dependent Variable: Log wages

	OLS	OLS full controls	FE	FE full contols
IT 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 5: IT employment and Non-IT employment

	IT employment	Non-IT employment
IT 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.

employees who use the IT systems and applications. The sum of IT experts and IT users reflect the total IT-employment. Then we calculate non-IT employment by subtracting IT-employment from total employment level.

Table 5 presents the IT index coefficients on IT employment and non-IT employment in the firm from fixed effects regressions. The coefficient of the IT index on the log of IT employment is 0.9 and statistically significant. The coefficient on the log of non-IT employment is insignificant. This implies that the positive relationship between ITs and overall employment is due to IT-related employment and not the remaining employment in the firm fixed effects regressions.

When we repeat the OLS and fixed effects regressions using advanced Internet use dummy instead of the IT Index, we obtained slightly higher coefficients on log of employment and IT employment. Table 6 reports the firm fixed effects regression results where the independent variable for IT 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 IT index and advanced Internet use measures, there is a significant positive relationship between IT use and IT employment and a non-significant relationship between IT and non-IT employment. The positive effects of IT on IT 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.

Table 6: Advanced internet Use

	Log Employment	Log IT Employment	Log Non-IT 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.

4.3 Lags of IT measures in four year panel

Next, we use the four year panel data (2007-2010) in order to estimate IT effects on IT and non-IT labor over a longer time period. We lack control variables for 2009 and 2010.[6] However, in the 2-year panel the coefficients do not change significantly when control variables are added since we are including firm fixed-effects. Firm fixed effects take care of observable and unobservable controls that are constant over time and including additional control variables do not affect the results significantly. Table 7 presents the results where the log IT employment and the log non-IT employment are regressed on the first and second lags of IT index and advanced Internet use. The first and second lags of IT variables are significant for the fixed regressions where the dependent variable is the log IT employment. The positive effects of IT use on IT employment decreases in magnitude over time. On the other hand, the effects of IT use on non-IT employment are significant using the lagged IT variables, and the magnitude increases over time. These results support that IT investments lead to an increase in IT workers for a while, and this effect decreases over time. The initial setup and use of these technologies might require more labor. As learning increases, the contribution of IT to IT-labor increases at a decreasing rate. IT investments can only increase other

[6] 2009 data will be available December 2012

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 IT investments on non-IT labor only using the lagged IT measures. Table 8 presents the lagged-effects IT on average wages. We find larger lagged-effects on wages that increases over time as hypothesized.

Related to the longer term effects of IT use on non-IT labor, we analyzed the effects on firm productivity. We use output per employee and value-added per employee as two measures of firm productivity. Table 9 presents the results where the dependent variable is log output per employee in Column 1 and log value-added per employee in Column 2. Here we estimated the current effect of IT measures on output and productivity. The IT measures and the productivity measures are not significantly correlated in the two-year panel. Table 10 presents the results of the effects of lags of IT measures on the productivity measures in the four-year panel. Similar to the non-IT employment results, the coefficients are significant and they increase over time. These results support the idea that IT use takes couple of years to lead to productivity gains that can increase the demand for non-IT employment.

These results constitute our main findings. IT use and IT-labor are complementary so we expect to observe higher levels of IT-employment with higher levels of IT use. There are direct immediate positive effects of IT use on the level of IT-employment. The lagged values of IT use have smaller coefficients on IT-employment. The reason for this can be lower need for maintenance labor and users as the new technologies become more established and learned by employees. There are no significant immediate effects of IT use on non-IT labor. The effects start to show up with the one-year lagged IT use variable and they increase with the two-year IT use variable. We also observe similar coefficients that increase over time for productivity and size variables. ITs take time to change other factors at the firm that will affect the demand for all types of labor. When additional years added to the data set, we can further establish the robustness of this time pattern.

Table 7: Four Year Panel: 2007-2010

Dependent Var: Log IT Employment

	(1)	(2)	(3)	(4)
Lag 1 IT Index	1.2542***			
	(0.1440)			
Lag 2 IT 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-IT Employment

	(1)	(2)	(3)	(4)
Lag 1 IT Index	0.1153			
	(0.3034)			
Lag 2 IT 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 8: Effects of lagged IT variables on wages

Dependent Var: Log wages

	(1)	(2)	(3)	(4)
Lag 1 IT Index	0.3857***			
	(0.1019)			
Lag 2 IT Index		0.5201***		
		(0.1373)		
Lag 1 Advanced Internet Use			0.6753***	
			(0.0344)	
Lag 2 Advanced Internet Use				0.7983***
				(0.0398)
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 9: Regressions of output and productivity measures

	(1) Log output	(2) Log value-added per employee
IT Index	0.0352	0.0812
	(0.0511)	(0.1069)
Advanced Internet Use	0.0285	0.0719
	(0.0334)	(0.0871)
Firm Fixed Effects	Yes	Yes
Observations	5570	5570

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

Table 10: Effects of lagged IT variables on output and productivity

Dependent Var: Log output

	(1)	(2)	(3)	(4)
Lag 1 IT Index	0.1004***			
	(0.0009)			
Lag 2 IT Index		0.3524***		
		(0.0781)		
Lag 1 Advanced Internet Use			0.0097***	
			(0.0211)	
Lag 2 Advanced Internet Use				0.2913***
				(0.0376)

Dependent Var: Log value-added per employee

	(1)	(2)	(3)	(4)
Lag 1 IT Index	0.2832***			
	(0.0988)			
Lag 2 IT 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

5 Generalized Propensity Score Matching of Firms

The relationships between IT use and employment/wages have potential endogeneity problems. We address this issue by conducting an analysis based on different assumptions. First, we use generalized propensity score matching that removes these observable biases. This method calculates the effects of IT 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. Second, we use instrumental variables to obtain further evidence on causality. We find different sets of instruments to be valid for different industries and technology use classifications within the same sector. Third, we analyze the relationship between current IT levels and past employment levels and find that past employment levels do not predict current IT levels. These findings provide further evidence against the presence of reverse causality.

We use the generalized propensity score (GPS) matching method to predict the IT 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 IT 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,

$$r(t, x) = f_{T|X}(t|x) \tag{4}$$

where T is the treatment level (IT 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 (IT Index) and GPS level R (Estimated IT Index),

$$\beta(t,r) = E[Y|T = t, R = r] \tag{5}$$

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

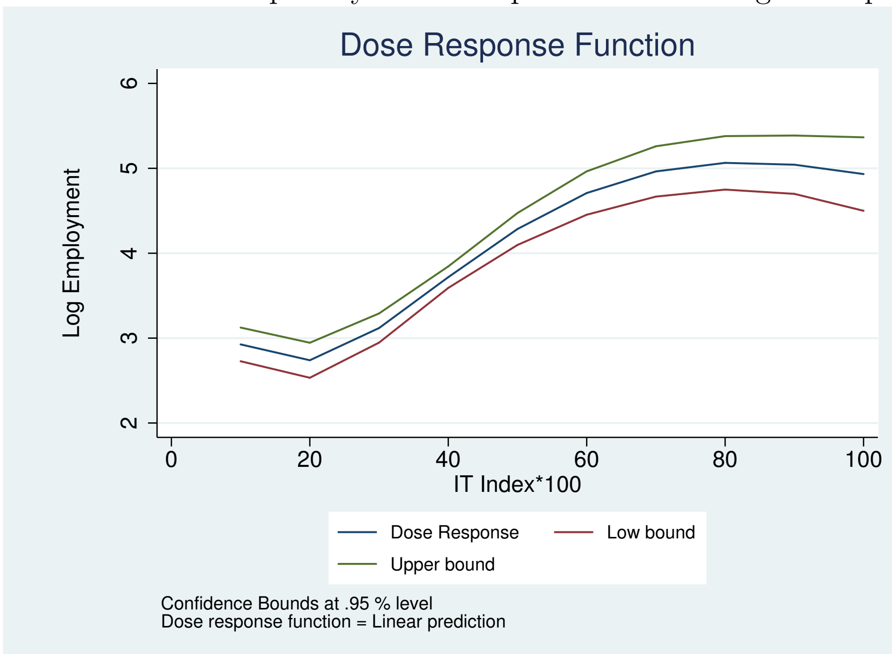
$$\mu(t) = E[\beta(t, r(t, x))] \tag{6}$$

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

Figure 1 presents the dose-response function estimated by the generalized propensity score method. Here, the IT Index levels range from 0 to 100, indicating the percentage of IT adoption and use intensity. The effect of the IT Index increases up to a level of 80%, where the effect is maximized with a 5% increase in employment level. Then the coefficient remains around 5% between IT Index levels of 80-100%.

Figure 2 presents the dose-response function estimates of the effects of the IT Index on wages. The IT Index causes an increase of between 9-10% in wages, and this relationship increases linearly. We also estimate a similar function for IT adoption, use, and skill indices separately. Figure 3 is the dose-response function of IT use index (a subsection of overall IT

Figure 1: Generalized Propensity Score: Dependent Var is Log of Employment



Index), which looks similar to the IT Index dose-response function. The effect is maximized around 80%, followed by a slight decrease.

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

Figure 2: Generalized Propensity Score: Dependent Var is Log of Wages

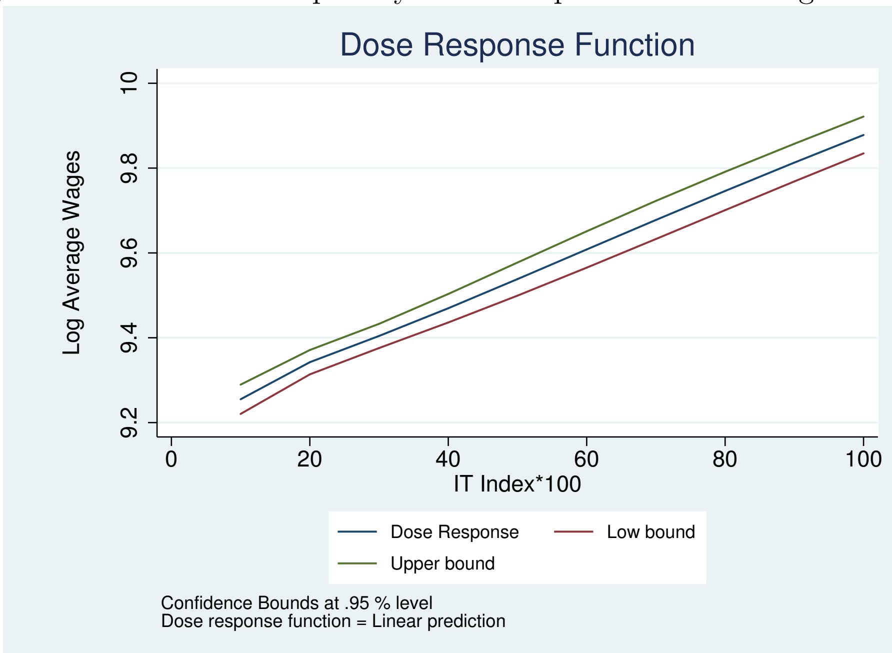


Figure 3: Generalized Propensity Score: Dependent Var is Log of IT Employment

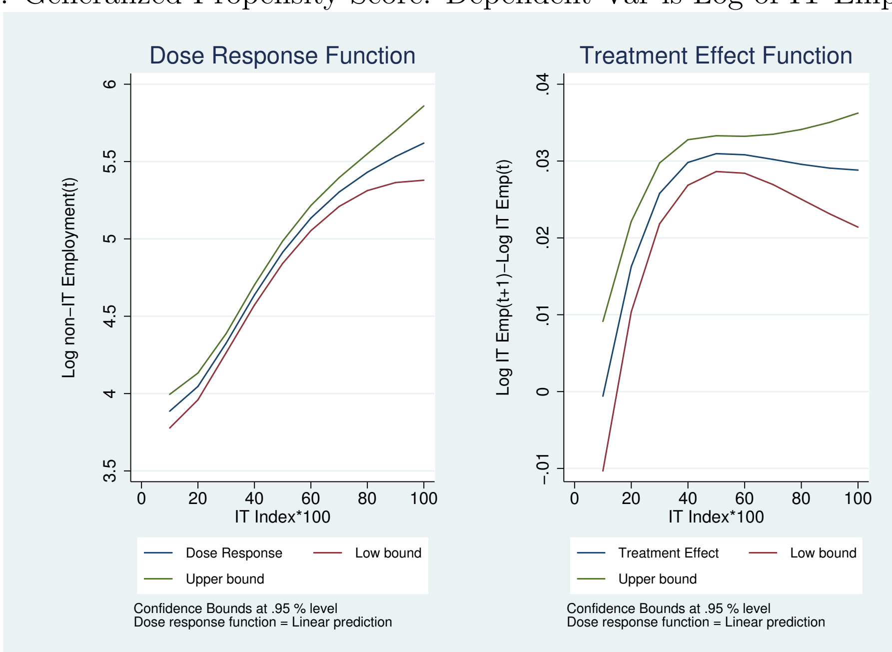
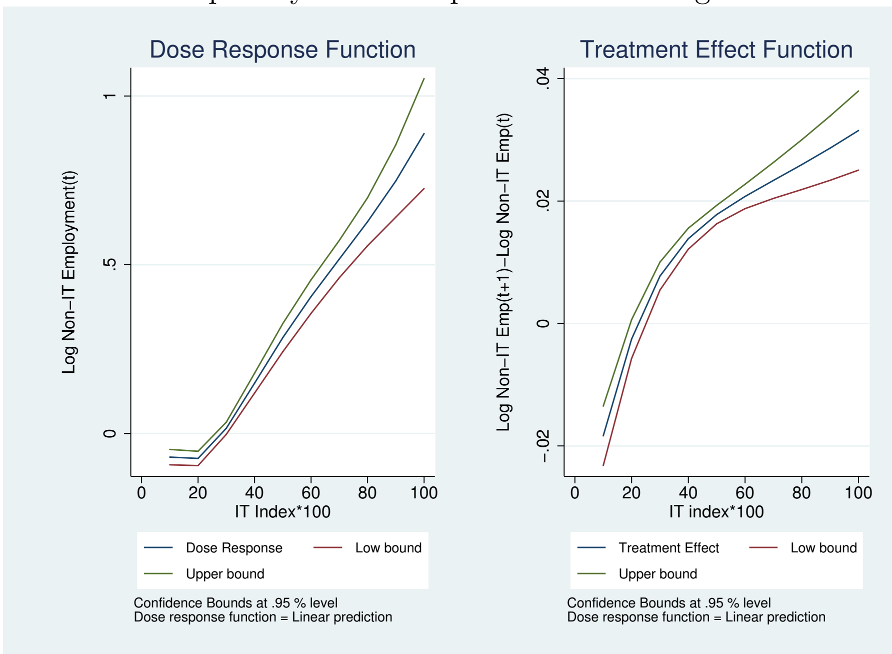


Figure 4: Generalized Propensity Score: Dependent Var is Log of Non-IT Employment



6 Instrumental Variables

Another way to address the endogeneiy issue is using instrumental variables method. This method requires finding variables (instruments) that are correlated with firm IT use bit not with the error term. These instruments are then used to estimate the endogenous regressors that eliminated the correlation between the endogenous regressors and the error term (Sargan 1958, Angrist and Imbens 1995, Angrist et. al. 1996) However, it is challenging to find valid instruments for firm level technology use as they are most likely be correlated with error term. Our strategy here is to test the validity of different instruments that are expected to work better for firms of different industries and technology intensity levels intuitively. We first pool all the firms and then separate them by industry and IT intensity levels.

We use 5 different instruments for firm level advanced internet use for all firms:

1. The city level IT 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 IT 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 11 presents the instrumental variable estimation results. Here, we 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 IT employment and average wages per employee. The coefficients on non-IT employment are not significant in the IV estimation. The standard errors are corrected for the panel observations and for heteroskedasticity.

6.1 Specification Testing of Instruments by Industries

Next, we 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. We use four 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.

Table 11: Instrumental Variable Estimation

			First Stage Regressions		
			Dependent Variable: Advanced Internet Use		
Instruments	city IT adoption	IT at foreign branch	city broadband penetration	first internet	fiber optic access
city it adoption	3.4121***				
	(0.1376)				
it 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 IT adoption	IT foreign branch	city broadband penetration	first internet	fiber
			Dependent Variable: Log IT 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-IT 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.

3. Wholesale: This is a big very industry in Turkey, as there are not too 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.

We used a 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 (Sargan 1958). We use the over-identifying restrictions test and orthogonality tests 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 12 summarizes the sets of IVs that are valid based on the above tests.

Table 13 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.

Table 12: Validity of IVs for different sectors

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

Table 13: IVs for different sectors

First Stage Regressions: Dependent Variable is Advanced Internet Use

	Manufacturing	Services	Wholesale	Exporting
city IT 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 IT 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				
Advanced Internet Use	1.2598***	2.9476**	1.6226***	1.3308***
	(0.5138)	(1.4567)	(0.3377)	(0.4021)
Dependent Variable: Log Non-IT Employment				
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 14: Validity of IVs for manufacturing and services sectors

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

6.2 More detailed classifications in manufacturing and services sectors

There is a significant within-sector heterogeneity. We further divide the manufacturing and services industries into smaller groups in order to remove some of the relevant heterogeneity within the sectors. We 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 14 shows the valid instruments for different sector classifications based on the specification tests. Table 15 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.

Table 15: 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 IT 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

	High-tech manufacture	Low-tech manufacture	Knowledge-intensive services	Less knowledge-intensive services
Dependent Variable: Log IT Employment				
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-IT 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 16: Past Employment

	Advanced Internet Use	IT 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

7 Robustness Checks

7.1 Relationship of ITs with past employment levels

We 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, we regress current advanced internet use levels on past employment levels. In Column 1 of Table 16, the dependent variable is advanced Internet use, and in Column 2 the dependent variable is the IT index. Past employment levels do not predict current IT levels. This evidence supports the causal interpretation from ITs to employment.

7.2 Effects on other labor variables

If the relationship between advanced internet use and IT employment is due to some unobservable factors, we might expect to see an accidental significant relationship with other

Table 17: 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)
IT 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

employment variables as well. Table 17 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.

7.3 Whether the firm hired an IT employee

The data set includes information on whether the firm hired one or more IT employee(s) (IT experts and IT users) within the last year. There is no information on how many people they have hired for these jobs. Table 18 presents probit regressions of dummy variables for whether the firm hired IT experts and IT 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 IT 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 IT expert. This also supports the mechanism of firms hiring new IT workers to maintain the technology.

Table 18: Probit for IT hire

	Hired IT User	Hired IT Expert	Hired IT Expert	Hired IT Expert
Advanced Internet Use	0.7143***	0.7428***	0.7175***	0.5907***
	(0.0461)	(0.0410)	(0.0423)	(0.1675)
Had a problem hiring IT labor			-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.

8 Discussion

8.1 Theoretical Implications

This paper analyzes how IT adoption and use affect employment and wages at the firm level. This question has not been addressed in the literature on the economic effects of IT that largely focused on the productivity and output effects of IT capital and IT investments. We use skilled biased technical change (SBTC) and resource complementarily theories in order to derive hypotheses on the effects of IT use on IT labor and non-IT labor. Using these models, we predicted that IT use and IT labor are have direct complementarities. Thus, higher levels of IT use would correspond to higher levels of IT employment and higher average wages at the firm. There is no direct relationship between IT use and non-IT labor. However, we predict that IT can affect non-IT employment through indirect channels such as changes in output and productivity. Lagged-effects of IT theory suggest larger increases in output and productivity over time, as there are complementary organizational changes and learning take place. Therefore, we expect IT use to have larger contributions to non-IT employment, output, and productivity in the longer term.

Besides the IT contributions literature, our paper relates to the extensive literature on labor demand and wage determination in economics. Several papers analyze firm and industry labor demand and wages (Sargent 1978, Hamermesh 1986, Hamermesh 1989, Berman et al. 1994, Blancflower et al. 1996). Our study focuses on the IT effects on the labor demand at the firm level by adding IT into the production function. Our study also relates to the lagged effects of IT literature. Most of these studies focus on the lagged effects of IT on productivity and find that even though there are some immediate contributions of IT, the lagged effects are greater. It takes time for IT effects to materialize for several reasons. The benefits of IT are accompanied by large and time-consuming investments in complementary inputs (Brynjolfsson and Hitt 2003). On the other hand, it takes time for employees to learn the new technologies (Armstrong and Sambamurthy 1999, Singh et al. 2012). We find similar lagged effects of IT on productivity. The contribution of IT on non-IT employment is also lagged and the magnitude of the contribution increases from one-year lag to two-years lags.

8.2 Empirical Implications

We used nationally representative data provided by the Turkish Statistical Institute to empirically test the predictions above. Detailed surveys were conducted from 2007-2010 on how much and for what purposes firms use IT and Internet technologies. We summarize several IT adoption and use indicators into an IT Index to measure how intensely these technologies are utilized within each firm. We find a significant positive association between IT use intensity, employment and wages within firms. The positive effects of IT on employment can be due to two mechanisms: the increase in IT employees with the adoption of new technologies, and overall expansion and productivity increase in the firm. We test for the presence of these mechanisms by dividing the total employment into IT and non-IT employment. IT use increases IT employment especially in the short term, while this effect seems to diminish over time. On the other hand, IT use does not significantly change non-IT employment in the two-year fixed effects models, but there are significant and increasing effects in the four-year fixed effects models. These results suggest that IT investments lead to firm expansion not immediately but over a longer period. Generalized propensity score matching, instrumental variable estimations and falsification tests supports the causal direction from IT investments to employment.

8.3 Public Policy Implications

There are important public policy implications of our results. There is an ongoing debate about the technologies' impacts on jobs. Recent federal policy programs have allocated $18 billion towards subsidizing the spread of broadband. The major goal of this policy is to increase employment levels. There are many aggregate studies on this issue and the evidence indicates that higher IT infrastructure in local areas are associated with more firms, higher average firm employment and higher average wages (Forman et al. 2012, Crandall et al. 2007, Kolko 2010, Atasoy 2012). However, microeconomic evidence on how these changes are taking place at the firm level is scarce. 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. Our results indicate that policies that aim to increase firm IT use can indeed increase employment levels. However, these effects can take time to be realized. We observe direct short-term increases in IT employment and indirect lagged increases in non-IT employment with higher IT use at the firm level. Since non-IT labor constitutes majority of the labor force, the employment effects that policy makers expecting might not be observed right away. We find that there are more positive and quicker impacts of IT on the complementary labor. This implies there will be larger employment effects on labor with more IT skills. Training of IT skills can be an important tool to realize larger and faster IT effects on employment levels. The use of government and company IT training programs can create more labor that complements IT, and thus larger and faster benefits of IT on employment levels.

8.4 Limitations and Suggestions for Future Research

This study has some limitations that raise some opportunities for future research. First, we use four-year panel data. Even though we find increasing effects of IT use with one and two year lags, this is still a relatively short time frame to analyze longer-term effects. IT adoption and use are relatively new topics of interest in Turkey compared to developed countries. Therefore, we lack consistent panel data to analyze longer-term effects of IT beyond four years. We also lack many control variables for the four-year panel (but we have a full set of control variables for the two-year panel). We find that this is not a problem for our estimates because we use fixed effects model to control for the unobserved factors that are constant over time. The tests we conduct using the two-year panel shows that adding control variables into the fixed effects models does not change out estimates. However, not having full set of controls for the four-year panel restricts our further analysis of generalized propensity score matching to the two-year panel sample.[7] Moreover, in this data set, we cannot distinguish different wages for IT and non-IT labor. We find that higher IT use is associated with higher wages, on average, for both IT and non-IT labor. Analyzing the differential effects on IT-labor wages and non-IT labor wages would an interesting opportunity for future research.

Our study provides important insights for future research. We theorize and estimate the relationship between IT use, IT-labor and non-IT labor. We provide evidence that there are increasing lagged-effects for non-IT labor, and decreasing lagged-effects for IT-labor even though we have limited number of lags in a four-year panel. These significant results in a short panel show the potential for analyzing longer-term panels as they are available.

[7] We will add one more year of IT survey (2011 survey) and one more year of business statistics survey for control variables (2009 survey) in December 2012. We will update our results with a five-year panel and three-year panel with full controls.

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