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LABOUR DEMAND ANALYSIS IN THE ICT SECTOR: EU COUNTRIES AND TÜRKIYE

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ABSTRACT

This paper is dedicated to specific research on the information and communications technologies (ICT) sector, where the variables determine labour demand in the European Union (EU) and Türkiye. The research aims to clarify the relationships between employment-generating firm growth that represents labour demand and the independent variables identified by the authors. For this purpose, our method analyses the factors affecting labour demand econometrically. In the study, a panel data set of 22 countries, including 21 EU countries and Türkiye, is used for the period of 2014-2019. The results show that there is a positive and significant relationship between employment in the ICT sector and real gross domestic product (GDP) per capita and frequency of internet use. In addition, the results show that the relationship between employment and wage level in the ICT sector is negative and significant. According to the results obtained from the Fixed Effects (FE) model, the elasticity coefficients of the independent variables in the model present for wages (1.53), GDP per capita (3.27) and frequency of internet use (1.60). Finally, we have discussed the results estimated by the Shadow Variable Least Squares (LSDV) method to measure the impact of each country on the overall variability in employment level. As a result of the study, when labour demand is associated with firm employment increase, the countries in the target geography where a significant and positive relationship was found are Belgium, Bulgaria, Croatia, Czechia, Estonia, Finland, Germany, Hungary, Italy, Latvia, Netherlands, Poland, Portugal, Romania, Slovakia, Spain, Sweden, and Türkiye.

KEYWORDS

ICT, Marshall Third Rule, Labour demand, EU, Türkiye, Panel data analysis, Fixed effects model, Least squares dummy variables

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1. INTRODUCTION

In the study, labour demand analysis in the information and communications technologies (ICT) sector in European Union (EU) countries and Türkiye is made. The relationship between the increase in labour demand and the growth of enterprises that increase employment by more than 10% is questioned in terms of different independent variables. In this query, in accordance with Marshall's 3rd Law in the literature, it is observed that the low elasticity of labour capital substitution is effective. The decrease in labour capital substitution elasticity brings the determinants of the increase in labour demand to the agenda for the ICT sector. When we associate the increase in labour demand with the growth of firms that increase employment by more than 10% according to Eurostat data; We get the opportunity to consider firm growth as a dependent variable. As independent variables in our model, gross domestic product (GDP) per capita, wages in the ICT sector and frequency of internet use were found to be significant. In this context, we can move on to the literature review covering Marshall's analysis in order to evaluate the impact of the increase in labour demand on firm growth and employment in EU and Türkiye countries.

2. LITERATURE

In the economic literature, the change in labour and capital shares within the production function has been the subject of many studies to determine the elasticity of derivative factor demand. First Alfred Marshall (1920), then J. R. Hicks (1932) and R.G.D. Allen (1938), then M. Bronfenbrenner (1961) and G.J. Stigler (1966) linked the reasons determining the elasticity of differential factor demand to four famous rules in their work. These rules are commonly referred to as the 'Marshall Rules' (Kennan, 1998).

Marshall-Hicks' first two rules; As factor substitution flexibility becomes easier in production, in other words, as it becomes easier to substitute the amount of labour used to produce the same amount of good with capital, derivative demand elasticity increases. Besides, the increase in the demand elasticity of the final good also increases the derivative demand elasticity of the said good. The reverse of the first two rules also applies. Therefore, as the amount of labour used in goods reaches a level that cannot be substituted by capital, or as the flexibility of factor substitution decreases, the elasticity of derivative demand also decreases due to the decrease in the elasticity of demand of the final good. Negative external economies emerge as the decrease in derivative demand elasticity will also adversely affect the demand for related goods in the economy. Marshall's fourth rule holds that the same applies to supply flexibility. That is, the positive effect on supply elasticity is linked to the elasticity of factors (Hoffman, 2009).

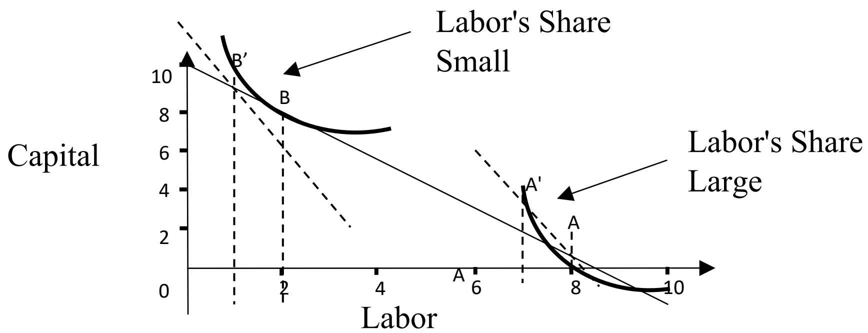
When evaluated in terms of the purpose of our study; Marshall's third rule is particularly important for understanding the impact of communication technologies on countries in the EU and Türkiye. According to this rule, it relates the elasticity of derivative demand in a sector to the share of labour in the total cost of that sector. According to Marshall, labour demand becomes more and more elastic as the share of labour in total costs shrinks, meaning that, it becomes less than 1 (Hoffman, 2009). The basic idea underlying this argument is according to the third rule; As a result of the elasticity of labour factor demand, any increase in wages leads to a greater long-term effect on average total costs (Şişman, D & Şişman, M., 2018).

2.1. Literature and ICT Sector

Although the production function indicates effective input-output combinations, it does not indicate which combination will maximize the entrepreneur's profits. In this sense, we need to consider the technology used in terms of the ICT sector we are dealing with. Therefore, the return of the technology used according to scale and the flexibility of substitution are important. The ICT sector is a sector where the yield increases according to scale as it creates external economies. Therefore, as the scale grows, specialization and efficiency are expected to increase. Afterwards, a significant decrease in costs is observed, and this trend is stronger, especially in capital goods used in sectors such as informatics. In summary, since the externality of the ICT sector is high, it is likely to create derivative demand for other sectors. Therewithal, another issue that characterizes technology is substitution flexibility. Substitution flexibility relates to the interchangeability of inputs to factor prices. In this sense, in the trade and investment relations between the two countries, labour costs in a large country are important compared to the small country, and labour costs in a small country are insignificant compared to the big country. Therefore, small-country labour costs are evaluated in terms of labour costs in large countries (Perloff, 2014).

As can be seen from Figure 1, let's assume that they produce on the same equivalent cost line according to different combinations of labour and capital. In this case, if in the large country (B) when the wages that determine the share of labour in the ICT sector rise, the firms do not enter into trade and investment relations with country A; must prefer point B', which has a lower substitution flexibility and has a higher co-cost line than point B, which cuts off the co-cost line. On the other hand, figure 1 is also *a small country*; after entering into an investment and trade relationship with the big country; At point A, *because it* has the *same substitution flexibility* over the same co-cost line, *higher labour* on demand *may prefer a combination of lower capital demand.* In this case, the cost of capital in a small country remains very low compared to the cost of labour (Hoffman, 2009).

Figure 1. Input adjustments to a change in factor prices when the share of labour in total costs differs.



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As a result, the demand for labour is greater, since the cost of capital of the small country is high before the trade. The increase in the demand for labour increases the tendency of wage growth in the small country compared to the big country. After the small country and the big country enter into a trade and investment relationship; Due to the high flexibility of substitution as a result of the rise in wages in the small country, as observed in figure 1, the use of more capital (A') will arise than labour, as the cost of capital decreases. Therefore, although wages rise in the small country, the cost of capital falls more, so the substitution flexibility is much greater in the big country than in the post-trade period. Because this situation explains the logic of trade between a small country (insignificant country) with a low wage and highly qualified labour in the EU and a big country or important country. In this case, the small country combines the supply of qualified labour with the cheap capital of the big country. *On the other hand, with the transition from point B to point A on the same iso-cost line in Figure 1 after the trade, both the coordination of growth rates in the EU and the integration of the Union are ensured through the ICT sector.* According to the studies, the convergence in the growth rates within the EU affects the EU growth rate more positively. In terms of developed countries, every 10% increase in the field of information technologies increases the growth rate by an average of 0.5-0.6%. In developing countries, the impact of the ICT sector on overall economic growth is much greater. In developing countries, including Türkiye, the effect of 10% growth in the ICT sector on overall growth can be up to 1% (İmamoğlu & Soybilgen, 2014). As a result of all these theoretical explanations in the study, in the EU and Türkiye in particular; We can evaluate it econometrically in terms of dependent variables such as the number of growth enterprises and the other independent variables such as GDP per capita, number of internet users and ICT wage index.

3. DATA SET AND ECONOMETRIC MODEL

Table 1 summarizes the definitions of dependent and independent variables in the model. All of the data used in the study were taken from the Eurostat database. Since the data set for the Labour Cost Index-Wages and Salaries in ICT sectors (lciwict) variable, which is presented as a component of the labour cost in the databases, is presented as a quarter, annual series are obtained by taking the average of all quarters in a given year for the variable in question. The datasets of the variables taken from the Eurostat database are presented in Table 1 with the headings indicated.

Table 1: Summary of Data Set and Variables

Key Variable	Description of Dataset	Unit of measure
Log(*emp*)	Employees in high-growth enterprises measured in employment (growth by 10%)	Person
Log(*lciwict*)	Labour Cost Index-Wages and Salaries in ICT sectors	Index, 2016=100
Log(*rgdpcap*)	Real GDP per capita	Euro
Log(*fia1w*)	Frequency of Internet Access Once a Week (including Every Day)	Percentage

Source: Eurostat (2023a, 2023b, 2023c, 2023d).

Wage elasticity of demand for labour in the labour market expresses the ratio of the percentage change in employment level to the percentage change in wages. Equation (1) expresses the mathematical form of labour demand's own wage elasticity:

$$\eta_{it} = \frac{\%\ change\ in\ employment\ in\ the\ labor\ market}{\%\ change\ in\ average\ wages\ in\ the\ labor\ market} \begin{cases} elastic & if\ |\eta_{it}| > 1 \\ inelastic & if\ |\eta_{it}| < 1 \\ unit\ elastic & if\ |\eta_{it}| = 1 \end{cases} \quad (1)$$

In that case, the classical linear panel data regression model that can be suggested for flexibility calculation can be defined as follows:

$$emp_{it} = \alpha_0 + \alpha_1 wage_{it} + \varepsilon_{it} \quad (2)$$

$$log(emp)_{it} = \beta_0 + \beta_1 log(wage)_{it} + u_{it} \quad (3)$$

In equation (2), *emp* refers to the employment level calculated as the number of persons, and *wage* refers to the average wage level. α_1, is the slope parameter that expresses the direction and severity of the change in employment volume created by a one-unit change in wages. When the system of equations in question is rearranged to reflect the relative changes between the variables, the full logarithmic model in the system of equations (3) is obtained. In this case, parameter β_1, in equation (2) expresses the elasticity coefficient explained in equation (1). ε_{it} and u_{it} are error terms.

In this study, panel data consisting of a total of 22 countries and 6-year series, including 21 EU countries and Türkiye, are used for the period of 2014-2019. In the study, we propose the panel data regression model expressed in equation (4) to calculate the wage elasticity of labour demand.

$$log\ (emp)_{\ it} = \beta_0 + \beta_1 log\ (lciw)_{\ it} + \beta_2 log\ (rgdpcap)_{\ it} + \beta_3 log\ (fia1w)_{\ it} + u_{it} \quad (4)$$

Here, *lciw* is the logarithm of the wage and salary index, the variable of which is calculated as a separate component of the labour cost. The numerical value was taken by the parameter β_1 to express the sensitivity of labour demand to wages. Other parameters in the model are the parameters of other variables that may affect the size of the total employment in the ICT sector. β_2 represents the effect of GDP per capita on total employment, and β_3 represents the effect of internet usage frequency on total employment. The *i* and *t* sub-indexes of the variables represent countries and years, respectively. ε is the error term. In addition, logarithmic transformation was applied to the series of all variables in the model in order to both eliminate the scale differences between the variables showing the geometric series feature and to obtain the elasticity interpretation from the summary statistics of the estimated parameter. All results in the study were calculated using the Stata17 package program.

Table 2 contains summary statistics of the variables. Since the unit size of the data set is i=22 and the time dimension t=6, it is seen that this panel data set is closer to the form defined as a short panel ($i > t$). The

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results show that the total number of observations for all variables is 132 and model (4) is a balanced panel data model.

Table 2: Summary Statistics of Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
emp	132	33978.61	46722.27	1099	254087
lciwict	132	107.32	20.23	77.98	245.88
rgdpcap	132	25496.44	17744.73	5470	84750
fia1w	132	79.18	11.71	44.87	96.75

3.1. Selecting the Appropriate Panel Data Model

The selection of the appropriate panel data model is important in terms of the reliability of the results obtained from the estimation of the regression model (2) and the validity of the coefficient interpretations. The choice in question depends on whether there are time-invariant factors that need to be controlled. In this case, the selection of the appropriate panel data model should be decided as a result of the tests performed. In panel data regression models, whether the unit effect or time effect has a significant relationship with the dependent variable is important in terms of determining the appropriate model. Therefore, the existence of unit and time effects should be tested by estimating the regression model (2) with FE and random effects (RE) models. In order to deal with unobservable heterogeneity in the model, it is necessary to examine unit effects, time effects, or both. Model (5) is the classical model without unit effects or time effects; models (6) and (7) are one-way models with unit or time effects, respectively; The model numbered (8) refers to the two-way panel data model in which unit and time effects are included in the model together.

$$y_{it} = \alpha + x_{it}\beta + \varepsilon_{it}, \qquad i = 1,\dots,N;\ t = 1,\dots,T \qquad (5)$$
$$y_{it} = \alpha_i + x_{it}\beta + \varepsilon_{it} \qquad i = 1,\dots,N;\ t = 1,\dots,T \qquad (6)$$
$$y_{it} = \gamma_t + x_{it}\beta + \varepsilon_{it} \qquad i = 1,\dots,N;\ t = 1,\dots,T \qquad (7)$$
$$y_{it} = \alpha_i + \gamma_t + x_{it}\beta + \varepsilon_{it} \qquad i = 1,\dots,N;\ t = 1,\dots,T \qquad (8)$$

In the study, first of all, the existence of unit effects and time effects were examined through FE and RE effects models in order to include unobservable heterogeneities according to units and/or time into the model.

$$emp_{it} = (\alpha + \mu_i) + \beta_{0it} \sum_{k=1}^{K} \beta_{kit} X_{kit} + v_{it} \qquad \text{(FE model)} \qquad (9)$$
$$emp_{it} = \alpha + \beta X'_{it} + (\mu_i + v_{it}) \qquad \text{(RE model)} \qquad (10)$$

In equations (9) and (10), μ_i, represents a FE and RE models specific to units or time that are not included in the regression. Here, FE applies when the unit effects are treated as an estimated parameter for each cross-sectional observation. RE occur when unit effects are treated as a random variable, such as the error term. In cases where there is no unit effect or time effect in the model, the pooled least squares (POLS) method in equation 5 can produce consistent estimates. However, in the case of unit effects in the model, the POLS estimator is not the best unbiased linear estimator. In that case, the appropriate estimation method should be decided as a result of tests performed on FE and RE estimators that take into account the existence of unit effects.

Table 3 shows the Anova-F (F), Breusch-Pagan Lagrange Multiplier (LM), Extended Breusch-Pagan Lagrange Multiplier (ALM), Likelihood Ratio (LR), and Score test statistics used to test for unit or time structure finding. The results show that the unit effects are significant and the H_0 hypothesis is rejected. However, the LM test statistic used to test for the presence of unit effects is not a reliable test when there is autocorrelation in the model. In cases where there is autocorrelation in the model, it is necessary to rely on ALM tests. According to the F test and LR test statistics to test the existence of one-way time effects on the FE and RE models, it is understood that the H_0 hypothesis cannot be rejected and there are no time effects.

Table 3. Testing for Unit and Time Effects

Tests Statistics	**Hypothesis**	**F**	**Wald**	**p-value**
Anova F	$H_0:\mu_i=0$	182.149	-	0.0000
	$H_0: \lambda_i=0$	1.17		0.3261
LM (Chi2_c)	$H_0: \sigma^2_\mu=0$		281.73	0.0000
ALM	$H_0: \sigma^2_\mu=0$		139.51	0.0000
LR (Chi2_c)	$H_0: \sigma_\mu=0$		311.3931	0.0000
	$H_0: \sigma_\lambda=0$		0	1.0000
	$H_0: \sigma_\mu=\sigma_\lambda=0$		332.7545	0.0000
Score (Chi2_c)	$H_0: \sigma_\mu=0$		8.8e+05	0.0000

In the estimation of a model (4), Hausman test statistics are relied on to select the appropriate model among FE and RE models. The test compares the difference between the coefficients of the two models and their variance-covariance matrices to determine which model is more efficient and consistent (Griliches et al., 1978). Table 4 summarizes the Hausman and Rhausman test statistics, which is the corrected version of the test for deviations from the assumption. It is thought that the Rhausman test gives more reliable results when there is autocorrelation, heteroscedasticity, and interunit correlation in the model. The results show that the H_0 hypothesis is rejected, the FE model is consistent and the RE model is inconsistent for model estimation.

Table 4. Hausman Test Results

Test	**Statistics**	**p-value**
Hausman	22.65	0.0000
Rhausman	17.43	0.0006
H_0: Difference in coefficients not systematic		

3.2. Summary of Deviations from the Assumption

For the reliability of the interpretations of the parameters calculated by the regression model (4), deviations from the assumption should be examined. In this context, examining the deviations from the

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assumption such as the normal distribution of error terms, inter-unit correlation, heteroscedasticity and autocorrelation is important for the efficiency and consistency of the estimated parameters.

3.2.1. Normal Distribution Test

The normal distribution of error terms is important in order to be able to rely on the confidence intervals of the parameters calculated over the classical model, FE and RE models and to interpret the parameters. Table 5 summarizes the normal distribution test results on the FE and RE models. According to all test results, the H_0 hypothesis cannot be rejected. That is, the residues are normally distributed. Since the error term in the RE model consists of a composite error term, a separate normal distribution test was performed. The test statistics calculated on the RE model show that the unit effect and error term are normally distributed.

Table 5. FE and RE Models Normal Distribution Test Results

Model	**Statistics**	**p-value**
Fixed effects model		
Jarque-Bera Normality test: (H_0: S=0, K=3)	3.016	0.2213
Random effects model		
Joint test for Normality on u: (H_0: S=0, K=3)	0.2213	0.2521
Joint test for Normality on μ: (H_0: S=0, K=3)	0.60	0.7407

3.2.2. Cross-Sectional Dependence Test

Cross-sectional dependence refers to the correlation between error terms calculated for each unit in panel data regression models. Table 6 contains test statistics that test the existence of a correlation between units over the FE model. The results show that the H_0 hypothesis that there is no inter-unit correlation for all tests cannot be rejected, therefore there is no inter-unit correlation. In the RE effects model, since all units come from random gravity, no correlation between units is expected (Yerdelen Tatoğlu, 2013). Table 6 tests the H0 hypothesis established as cross-section independence in small T and large N panel data models, applying the testing procedure suggested by Friedman, (1937) and (Pesaran, 2004)[1]. The results show that the H_0 hypothesis is rejected and there is no cross-sectional dependence.

Tablo 6. FE Model Cross-Section Dependency Test Results

Test Type	**Statistics**	**p-value**
Friedman	8.312	0.9937
Pesaran	1.446	0.1481

3.2.3. Heteroscedasticity Test

Heteroscedasticity occurs when the variability of residuals in a regression model is not constant across the independent variable range (Greene, W. H., 2003). It can lead to erroneous standard errors and confidence

[1] The comparative performance of these tests for small samples was examined by De Hoyos & Sarafidis (2006).

intervals, as well as biased and inefficient estimates of the regression coefficients. In this case, estimators that are resistant to heteroscedasticity in the model should be used.

Table 7 contains test statistics that analyze the presence of varying variance through the FE model and the RE model. Heteroskedasticity was analyzed with the modified Wald[2] test in the FE model and Levene (1960), Brown and Forsythe (1974) tests in the RE model. The Test column shows the type of tests performed and their degrees of freedom (df). According to all test statistics, the H_0 hypothesis is rejected. It is seen that the variances of all units are different from each other.

Table 7. FE and RE Models Heteroskedasticity Test Results

Model	Tests	Null Hypothesis	Statistics	p-value
SE	Wald Test (chi2 (23))	H_0: $\sigma_i^2 = \sigma^2$	1691.39	0.0000
TE	W0 df (21, 110)	H_0: δ=0	3.4576855	0.00001153
	W50 df (21, 110)	H_0: δ=0	1.8439772	0.0222974
	W10 df (21, 110)	H_0: δ=0	3.4576855	0.00001153

3.2.4. Autocorrelation Test

Autocorrelation testing in panel data models helps determine whether the error terms are correlated over time. Autocorrelation occurs when error terms are correlated at different time delays. This can affect the validity of statistical inference, leading to biased and inefficient estimates of model parameters. If there is autocorrelation in the model, an appropriate resistance estimator should be chosen. Table 8, Bhargava et al. (1982) and Baltagi and Wu, (1999) summarize the Durbin-Watson and locally best invariant (LBI) test statistics. Although critical values are not given for these tests in the literature, if the calculated value is less than two, it is interpreted that autocorrelation is important (Yerdelen Tatoğlu, 2013). The results obtained from the FE and RE models show that there is autocorrelation in the model.

Table 8. FE and RE Models Autocorrelation Test Results

Model	Tests	Null Hypothesis	Statistics
FE	Bhargava et al. Durbin–Watson	H_0: ρ=0	1.0095698
	Baltagi–Wu LBI	H_0: ρ=0	1.4340195
RE	Bhargava et al. Durbin–Watson	H_0: ρ=0	1.0095698
	Baltagi–Wu LBI	H_0: ρ=0	1.4340195

3.3. Fixed Effects Model Estimation Results

Table 9 shows the results obtained using estimators that are resistant to deviations from the assumption in the FE model. The Robust column summarizes the results of the estimation method proposed by Eicker

[2] Following W. Greene (2000), a modified Wald statistic was calculated for group-by-group variance in the residuals of a fixed-effects regression model.

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(1967), Huber (1967), and White (1980) which provides robust standard errors in case of differential variance in the model. Group Estimator summarizes the results of the estimation method proposed by Arellano (1987), Froot (1989) and Rogers (1993) which provides robust standard errors for differential variance and autocorrelation in the model. LSDV, on the other hand, includes the results obtained from the estimation method, which allows the calculation of the employment of each country and includes the countries in the model as an independent variable. The results obtained on the basis of countries with the said estimation method are summarized in Table 10.

Table 9: Resistive Standard Errors Estimated by the Fixed Effects Model

Variable	**Within Estimator**	**Robust**	**Within Group Estimator**	**LSDV**
loglciwict	-1.532968***	-1.532968***	-1.532968***	-1.532968***
logrgdpcap	3.27425***	3.27425***	3.27425***	3.27425***
logfia1w	1.595689***	1.595689**	1.595689**	1.595689***
constant	-22.52544***	-22.52544**	-22.52544**	-25.10046***
R^2_Wald	0.3837	0.3837	0.3837	0.9747
F	22.21***	11.76***	11.76***	171.78***
Df	(3,107)	(3,21)	(3,21)	(24, 107)
corr (ε_i, Xβ)	-0.9029	-0.9029	-0.9029	-
Sigma_ε	2.7154353	2.7154353	2.7154353	-
Sigma_μ	0.20403572	0.20403572	0.20403572	-
ρ	0.99438579	0.99438579	0.99438579	-

Note: ** denotes significance at the 5 %-level and *** at the 1 %-level, respectively.

According to the results in Table 9, the wage elasticity of labour demand was calculated as approximately (1.53) in the negative direction for the entire sample group. The effects of GDP per capita and internet usage frequency on employment were calculated as approximately (3.27) and (1.60), respectively. According to the results of the F test, which tests the significance of the model in general, it is seen that the model estimated according to all estimation methods is significant. The R2 value calculated on the FE model was approximately (0.38). Due to the dummy variables included in the model for each unit in the LSDV method, the R2 value was calculated as approximately (0.97), which is a higher value. The value of ρ represents the share of the variance of the unit effect error item within the combined error variance (Yerdelen Tatoğlu, 2013). Sigma_ε and Sigma_μ summarize the standard error of the residual error element and the unit error element, respectively.

Table 10 shows the negative or positive impact of each country on total employment. Looking at the output above, firstly, the dummy variable, which is one less than the number of countries, was included in the model in the LSDV method and an estimate was made. According to the LSDV results, the individual impact of all countries on employment is significant except for Slovenia. The parameter values calculated for Austria, Denmark and Luxembourg summarize that the effects of these countries on firm employment are negative and significant. On the other hand, the values calculated for Finland, Bulgaria, Croatia, Czechia, Germany, Hungary, Italy, Netherlands, Poland, Portugal, Romania, Slovakia, Spain, and Türkiye show that these countries are positive and significant in terms of ICT employment growth.

Table 10: Estimation Results Obtained by LSDV Method

Country	Statistics	Country	Statistics	Country	Statistics
Bulgaria	7.398748***	Germany	3.315425***	Finland	0.654325***
Türkiye	6.527801***	Czechia	3.106697***	Sweden	0.423388***
Romania	6.335988***	Croatia	3.048318***	Belgium	0.256089**
Poland	5.765579***	Slovakia	2.782062***	Denmark	-0.47637**
Hungary	4.563988***	Italy	2.766837***	Luxembourg	-4.305254***
Latvia	3.704941***	Estonia	1.954131***	Austria	-25.1005***
Portugal	3.578002***	Netherlands	1.008752***		
Spain	3.539458***	Slovenia	0.701524		

Note: ** denotes significance at the 5 %-level and *** at the 1 %-level, respectively.

4. Conclusion and evaluation:

In accordance with Marshall's 3rd Rule, which was introduced in the literature about 100 years ago, the ICT sector is a sector with a very low elasticity of substitution of the capital employed by the labour factor. Therefore, the very low elasticity of substitution between labour and capital used in the ICT sector was found to be important in terms of revealing the determinants of labour demand. In this study, the employment level data of firms that increase employment by more than 10%, representing labour demand, is considered as a dependent variable. Eurostat data is used in the model. The independent variables that we think affect the labour demand are; The level of GDP per capita in the countries studied (22 countries) was determined as the ICT Wage Index and frequency of internet use. The results of the econometric model we used in the study are in accordance with Marshall's low factor substitution elasticity analysis; It has been determined that the demand for labour in the ICT sector in Türkiye and EU countries is directly proportional to the sector structure that increases the employment in the companies. In general, in the relevant countries; As the determinants of labour demand, GDP per capita and frequency of internet usage are in a significant and positive correlation, respectively. From the point of view of creating derivative demand, the increase in GDP per capita leads to an increase in employment, that is, an increase in labour demand, more than itself. On the other hand, the increase in the number of internet users in the EU and Türkiye may cause an increase in labour demand almost as much as itself. The fact that the increase in wages is inversely proportional to the growth of the firm is meaningful in terms of adapting Marshall's analysis to the present. Because the sensitivity to wages is very high in the ICT sector, which has low factor substitution flexibility. Therefore, we can deduce that the relatively low wage structure in the ICT sector has a greater impact on labour demand. As a result, among the independent variables determining the demand for labour in the model, the countries where wage, internet usage frequency and GDP per capita have a high effect on firm employment are respectively; Bulgaria, Türkiye, Romania, Poland, Hungary, Latvia, Portugal, Spain, Germany, Czechia, Croatia, Slovakia, Italy, Estonia, Netherlands, Finland,

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Sweden and Belgium. Denmark, Luxemburg and Austria, on the other hand, are found to be in a significant but negative relationship (inverse correlation) in terms of explaining our model. This necessitates working on the fact that the labour demand in the ICT sector in those countries is realized from other countries. Among the countries studied, Slovenia was not found to have a significant effect on labour demand. We think that Slovenia should be examined in a separate study.

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