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INFORMATION AND COMMUNICATION TECHNOLOGIES AND EMPLOYMENT GENERATION IN TURKISH MANUFACTURING INDUSTRY

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Abstract

This study aims to examine the impact of the use of Information and Communication Technologies (ICT) on employment generation in the Turkish manufacturing industry. This study is said to be the first attempt in exploring the impact of ICT on employment generation in Turkish manufacturing industry at the firm level. The analysis is based on firm level data obtained from Turkish Statistical Institute (TurkStat) and covers the period from 2003 to 2013. The data used in the analysis includes all firms employing 20 or more employees in Turkish manufacturing industry. Our findings based on system GMM estimations show that ICT has employment-enhancing effects in Turkish manufacturing. Moreover, our results provide the evidence that tangible ICT capital has stronger employment generation impact than that of intangible ICT capital in medium-tech and low-tech industries.

JEL Classifications: D24, J20, L60, O14.

Keywords: Employment, ICT, manufacturing industry, Turkey.

ملخص

تهدف هذه الورقة إلى دراسة أثر استخدام تكنولوجيات المعلومات والاتصالات على توليد العمالة في الصناعة التحويلية التركية. ويقال إن هذه الدراسة هي أول محاولة لاستكشاف أثر تكنولوجيا المعلومات والاتصالات على توليد فرص العمل في الصناعة التحويلية التركية على مستوى الشركة. ويستند التحليل على بيانات مستوية من معهد الإحصاء التركي (توركستات) ويغطي الفترة من عام 2003 إلى عام 2013. وتشمل البيانات المستخدمة في التحليل جميع الشركات التي توظف 20 موظفا أو أكثر في الصناعة التحويلية التركية. وتبين النتائج التي توصلنا إليها استنادا إلى تقديرات نظام الرصد العالمي أن تكنولوجيا المعلومات والاتصالات لها تأثيرات على العمالة في الصناعات التحويلية التركية. وعلاوة على ذلك، توفر نتائجنا الدليل على أن رأس المال الملموس لتكنولوجيا المعلومات والاتصالات له تأثير أقوى على توليد فرص العمل من رأس المال غير الملموس لتكنولوجيا المعلومات والاتصالات في صناعات التكنولوجيا المتوسطة والتكنولوجيا المنخفضة.

1. Introduction

There is no doubt that the use of information and communication technologies (ICT) is increasing in all industries of manufacturing. Although the impact of ICT use on productivity of the firm is quite clear, there is no consensus in the empirical literature on the employment effects of ICT since both compensation mechanisms and substitution effects are supported substantially in the previous studies.

Starting from ambiguous results in the empirical literature on employment creation or destruction of ICT, this project examines the impact of ICT use on employment generation in the Turkish manufacturing industry by using labor demand estimation at the firm level. The effect of ICT usage on employment is also analyzed for different sub-sectors (2-digit NACE) in manufacturing industry to see whether the impact varies in different sub-industries. Moreover, in this study, the impact of different ICT capital (tangible vs. intangible) on labor demand is explored. This research contributes in filling the empirical gap by estimating labor demand equations at the firm level in Turkish manufacturing from a dynamic perspective. The findings of this research will provide some critical insights for policy implication.

This study is said to be the first attempt at exploring the impact of ICT on employment generation in Turkish manufacturing at the firm level. The analysis is based on firm level data obtained from Turkish Statistical Institute (TurkStat) and covers the period from 2003 to 2013. The data used in the analysis includes all firms employing 20 or more employees in Turkish manufacturing industry.

In this study, we estimate labor demand equation derived from a production function with constant elasticity of substitution (Van Reenen, 1997; Conte and Vivarelli, 2011) by using OLS, fixed effects (considering unobserved heterogeneity), and GMM (considering probable endogeneity in the model).

In the next section, we briefly review the literature. Section 3 presents the data and descriptive statistics. Empirical strategy is introduced in section 4. Section 5 is reserved for the results and discussion. Robustness check of the results is discussed in Section 6. Finally, we summarize the findings in the conclusion.

2. Literature Background

There are two dominant theoretical approaches in this literature, where the effects of technological change on employment are researched: compensation mechanism and substitution effect.

Compensation mechanism argues that labor-saving effect of technological progress may be compensated via some mechanism by market oriented indirect effects. Moreover, it asserts that compensation mechanisms will dominates and thus technological change lead to employment generation in the long run (see Vivarelli, 1995; Petit, 1995; Vivarelli and Pianta, 2000; Pianta, 2001, 2004; Machin, 2003; Vivarelli, 2007; Piva and Vivarelli, 2009). Compensation mechanism about employment impact of technological changes (especially ICT for today's economies) may be listed as follows: the compensation via additional employment in the capital goods sector, via decrease in prices, via new investments, via decrease in wages, via increase in incomes, via new products. Specifically, the use of new technologies creates new jobs in the capital sectors where the new machines are produced (additional employment in the capital goods sector); innovations lead to a decrease in the cost of production, and decreasing prices generate a new demand for products, thus additional production and employment (decrease in prices); due to technical progress and decrease in prices, innovative entrepreneurs accumulate additional profits. These profits lead to new productions by investment, hence new jobs will be created (new investments); labor-saving technologies may be compensated in labor market via proper price adjustments within a neoclassical framework. Free competition and substitutability between labor and capital lead to a decrease in wages and thus increase in labor demand (decrease in wages); within a Keynesian and Kaldorian framework, cost savings due to technical change may be translated into higher incomes and thus higher consumption. Main rationale of the last mechanism that unions participate in the sharing of the gain of technological progress and this portion of the cost savings due to innovation should be considered. Therefore, it leads to an increase in employment (increase in incomes). Finally, technical change can assume the form of creation and commercialization of new products, and hence additional jobs are created (new products).

Substitution effect, on the other hand, points out the labor-saving impact of ICT. Specifically, technological change creates employment polarization, in which skilled labor-unskilled labor effects are significantly emerged. Thus, it leads to decrease in employment (inter alia, see Rifkin, 1995; Hammer, 1990; Rackhman, 1999; Autor, Levy, and Murnane, 2003; Ford, 2009). Basic effects and mechanism in substitution effect are job destruction, skill biased technological change, task oriented jobs, and polarization. According to this approach, employment destruction is emerged as traditional industries improve their technology. The basic intuition is that new technologies require less labor. Moreover, polarization argument points out that although routine tasks are replaced by machines, usually mid-skill workers are required to perform routine tasks. However, lowest skill labor continues to be employed in personal services, which may not be easily automated. Hence, labor market polarization emerged due to the fact that ICT innovation destructs mid-skill jobs.

There is no consensus in the empirical literature on the employment effects of ICT since both compensation mechanisms and substitution effect are supported substantially in the previous studies. For instance, Evangelista (2000), Simonetti et al. (2000), Spiezia and Vivarelli (2000), Harrison et al. (2005), and Smihula (2010) show that compensation mechanisms work; besides Freeman (1988), Blackburn et al. (1990), Murphy and Welch (1992), Berman et al. (1994 and 1998), Goos et al. (2009), Acemoğlu and Autor (2011) focus on substitution effects and confirm them.

To the best of our knowledge, Atasoy (2011) is the only study that examines the effect of ICT on employment in Turkey. Basic finding of that study is that use of ICT increases both employment and wages in Turkey. However, Atasoy (2011) has some shortcomings and limitations. First of all, the data used in that study covered only 2007-2008. Secondly, it ignores dynamic effects by making use of a static panel data estimation technique. Thirdly, it ignores the dynamics of labor demand structure by using an ICT index. Finally, sectoral focus was quite aggregate level.

3. The Data and Descriptive Statistics

The analysis was conducted by using the richest data available at firm level in Turkey. The data used in this project includes the micro-level databases of the Turkish manufacturing industry obtained from the Turkish Statistical Institute (TurkStat). TurkStat does not permit the database to be removed from its premises and requires “a Protocol of data confidentiality and data security”. We have the protocol need to work at TurkStat and use the micro data. Thus, all empirical analyses in this project were conducted in Micro Data Research Center of TurkStat in Ankara due to data confidentiality and confident data security. TurkStat allows the researchers to take the results of their analysis out after controlled by related Departments of TurkStat. However, the results and the interpretations expressed in this study are exclusive responsibility of the authors, and by no means represent official statistics.

Starting from 2003, TurkStat annually conducted the survey for *Annual Industry and Service Statistics*, which provides firm level information on many firm-specific variables. This database covers all enterprises with 20 or more employees and a sampling census of enterprises with 19 or less employees in Turkey for each year for the period 2003-2013. The data is provided for each year, separately. We will use a sample, which appends Annual Industry and Service Statistics for the period 2003-2013. We converted all databases of different years into a common data format and check the consistency issues.

The dataset includes a rich body of information for each firm; including number of employees, wages, volumes of inputs and output, investment activities, and industrial detail.

All monetary variables are expressed in Turkish Lira with current prices. We convert all nominal variables into real variables by using 4-digit industry level deflators with 2003 as the base year. The classification of enterprises by type of activity was determined by NACE Rev. 2 for all sectors. Since we use panel-data estimation techniques, and so we need to track a firm throughout all years until exit the industry, we restrict our sample with only the firms with 20 or more employees due to their full enumeration in each year. Moreover, the firms that cannot be tracked for at least two consecutive years were excluded from the final sample. This is because our empirical analysis utilizes a dynamic labor demand model and relies on lagged values of regressors for identification as explained in the empirical strategy of this study (section 4).

Our resulting sample is an unbalanced panel of 43,567 Turkish manufacturing firms employing more than 19 employees over the 2003-2013 period, corresponding 185,180 firm-year observations.

Table 1 provides some indicators for relative importance of manufacturing industry in Turkish economy. For the period 2003-2013, annual average number of total firms in Turkish manufacturing sector is more than 300,000, rising from 236,275 in 2003, reaching 340,438 in 2013. The share of manufacturing employment is 18.8 % on average whereas manufacturing output (GDP) share is 18.3 %. Annual average growth rate of manufacturing employment is just 2.1 % although its output growth is 5.8 % for the same period.

As it is mentioned above, we restrict our sample with only the firms with 20 or more employees due to their full enumeration in each year. Table 2 illustrates the number of firms in the sample. The number of firms in the sample, with a yearly average of 20,529, rose from 14,067 in 2003 to 19,984 in 2006, and declined to 16,442 in 2009. Then, it steadily increased for the period 2010-2013, reaching 28,036 in 2013. According to technological intensity classification of Eurostat (Eurostat, 2015), low-tech manufacturing firms constituted the largest share in our sample with 53.2 % on average. The share of medium-tech manufacturing firms is 45.4% whereas that of high-tech manufacturing firms is only 1.4 percent.

Table 3 show the relative shares firms included in our sample out of total employment and total production. As it can be seen from the table, the firms with 20 or more employees constitute 77.5 % of manufacturing employment, 88.7% of output, and 90% of value added. These figures clearly reveal that our sample is broadly representative for Turkish manufacturing industry.

Table 4 presents the distribution of firms by 2-digit sectors for the manufacturing industry. Wearing apparel (14) industry has the highest share in Turkish manufacturing with respect to both the number of firms and the size of employment. This industry is followed by textiles (13), food products (10), and fabricated metal products, except machinery and equipment (25) industries, respectively. On the other hand, food products (10), basic metals (24), motor vehicles, trailers and semi-trailers (29), and textiles (13) have highest shares with respect to output, respectively.

Distribution of firms and their relative shares with respect to employment, output and value added for different technology intensive industries are presented in Table 5. The table shows that the firms operating in low technology industries employ 52.4% of total manufacturing employment. 44.9% of the employment is in medium technology sector. High-tech firms constitute only 2.8% of Turkish manufacturing employment. On the other hand, the largest share of output and value added in total manufacturing belongs to medium technology sector.

Figure 1 shows evolution of employment structure in Turkish manufacturing for the period 2003-2013. Our data show that the manufacturing employment has been increasing for both of the series, all firms and the firms with 20 or more employees, except of the crisis year 2009.

3.1 Construction of capital stock

The capital input is defined theoretically as the services of capital goods in value terms. Since capital stock series is not available in the data, we need to make some assumptions and use some proxy variables to construct capital stock. The data used in this study includes only information on investment and depreciation allowance. Following Taymaz et al (2008), Üçdoğruk-Gürel and Kılıçaslan (2016), capital stock series are constructed by using the perpetual inventory method as follows:

$$\boldsymbol{K_{it} = (1 - d)K_{it-1} + I_{it}} \tag{1}$$

where K, I, and d stand for capital, investment and depreciation rate, respectively.

However, since the data does not contain information on capital stock in any year we also need to construct initial capital stock series for each firm as follows:

$$\begin{aligned} \boldsymbol{D_{it}} &= \boldsymbol{dK_{it}} \\ \boldsymbol{K_{i0}} &= \boldsymbol{D_{i0}/d} \end{aligned} \tag{2}$$

where D is depreciation value.

Therefore, we construct capital stock series for each firm according to Equation (2) for a firm's entry year (t=0), and according to Equation (1) for after entry (t>0).

Moreover, investment data is available in detailed sub-categories. There are 9 different investment items within the context of tangible investment; including lands and buildings, total construction of residential and non-residential structures, infrastructure, machinery and equipment; transport, computing and communications equipment, and other tangible investments. With regard to intangible investment, there are 4 different investment items; including computer software, purchased patents, intellectual property rights and licenses, and goodwill.

We compute four investment variables. Specifically, we define the investment item on office and computing equipment and communication equipment as tangible ICT investment whereas computer software is defined as intangible ICT investment. On the other hand, the aggregation of all other tangible investment items is defined as tangible non-ICT investment. Finally, intangible non-ICT investment equals to summation of intangible investment items other than computer software.

On the other hand, depreciation value in the data is in aggregate terms, not in detailed sub-categories for investment. Since we need separate depreciation values for each different kind of capital, we assume the ratio of each investment variable is equal to corresponding capital stock ratio. For example, we first found the ratio of tangible ICT investment out of total investment; then, multiplied tangible ICT investment ratio with the total depreciation value to obtain the firm's tangible ICT depreciation. We compute separate deprecation values for all other capital types in the same way. Hence, we created four different depreciation values for each firm and year.

We constructed separate series at firm-level for tangible ICT capital stock, intangible ICT capital stock, tangible non-ICT capital stock, and intangible non-ICT capital stock. We used 7.5% as a depreciation rate for tangible non-ICT capital stock, and 25% for tangible ICT capital stock, intangible ICT capital stock, and intangible non-ICT capital stock series.

Table 6 illustrates relative importance of ICT use and ICT capital in Turkish manufacturing for the period 2003-2013. On average, 76.0 % of firms have positive ICT capital. In other words, 76.0 percent of the manufacturing firms use ICT. However, 47.2 % is the share of ICT capital out of total capital in manufacturing. The share of tangible ICT capital is 36.1 % in the total capital whereas it is 11.1% for intangible ICT.

4. Empirical Strategy

This is the first study to investigate the impact of ICT capital on employment within a labor demand framework in Turkish manufacturing industry. To investigate the effects of ICT on employment for a perfect competitive industry, we use a derived labor demand equation based on a production function with constant elasticity of substitution, which is consistent with the empirical literature (Van Reenen, 1997; Conte and Vivarelli, 2011):

$$Q = T\left[(AL)^{\sigma-1/\sigma} + (BK)^{\sigma-1/\sigma}\right]^{\sigma/\sigma-1} \tag{3}$$

In Equation (3), Q is the output; L and K denotes labor and capital, respectively; T denotes Hicks-neutral technology parameter, A denotes labor augmenting Harrod-neutral technology; and B denotes capital augmenting Solow-neutral technical change. The following first order condition is obtained by assuming real wages equal to marginal productivity of labor:

$$\mathbf{ln}\boldsymbol{L} = \mathbf{ln}\boldsymbol{Q} - \boldsymbol{\sigma}\mathbf{ln}(\boldsymbol{W}) + (\boldsymbol{\sigma} - \mathbf{1})\mathbf{ln}\boldsymbol{A} \tag{4}$$

where W is real wages. Note that, following Berman et al. (1994) and Pantea et al. (2014), we treat capital as a quasi-fixed input that is said to be a reasonable assumption in the short run. This assumption also helps in avoiding potential problems in measuring the cost of capital.

This standard framework may be augmented by adding some proxies for the unobserved labor-augmenting technology component (A) by taking ICT use of the firm into account. One way to proxy ICT use is to take ICT part of total capital, called ICT capital. Moreover, one can define a dynamic model by adding lagged value of labor into the equation in order to consider costs of labor adjustments due to firm's attrition and delays in hiring/firing workers (Lachenmaier and Rottman, 2011).

Our empirical approach employs a dynamic specification in a panel data context to account significant lagged effects of the dependent variable that determine serial correlation in itself. The augmented labor demand equation may be expressed as follows:

$$\begin{aligned}\mathbf{ln}\boldsymbol{L}_{\boldsymbol{it}} = {} & \boldsymbol{\alpha} + \boldsymbol{\beta}_{\mathbf{1}}\mathbf{ln}\boldsymbol{L}_{\boldsymbol{it-1}} + \boldsymbol{\beta}_{\mathbf{2}}\mathbf{ln}\boldsymbol{W}_{\boldsymbol{it}} + \boldsymbol{\beta}_{\mathbf{3}}\mathbf{ln}\boldsymbol{Q}_{\boldsymbol{it}} + \boldsymbol{\beta}_{\mathbf{4}}\mathbf{ln}\boldsymbol{ICT}_{\boldsymbol{it}} + \boldsymbol{\beta}_{\mathbf{4}}\mathbf{ln}\boldsymbol{NonICT}_{\boldsymbol{it}} \\ & + (\boldsymbol{\varepsilon}_{\boldsymbol{i}} + \boldsymbol{\alpha}_{\boldsymbol{t}} + \boldsymbol{u}_{\boldsymbol{it}})\end{aligned} \tag{5}$$

where the subscripts i and t refer firms and years, respectively. L_{it} is the number of employees, L_{it-1} denotes the lagged number of employees, W_{it} is real wage, Q_{it} represents real output. Considering the uncertainty in the effect of ICT capital on employment, we include some alternative ICT_{it} variables as a technology component within the labor demand model. To this end, we use ICT capital variable. Also, we specify alternative models with tangible ICT capital and intangible ICT capital. Note that we control non-ICT capital (conventional capital) in all models. The variable ε_i and α_t denotes time invariant firm specific effects and time specific effects, respectively. The last term u_{it} is idiosyncratic error component.

To investigate the effects of ICT use on employment, Equation (5) will be estimated by using OLS, fixed effects (considering unobserved heterogeneity), and GMM (considering probable endogeneity in the model).

The assumption of strict exogeneity of the estimators is violated in a dynamic model. The existence of firm specific effects in labor demand equation above creates a correlation between the lagged dependent variable and the individual fixed effect. Using ordinary least squares gives inconsistent and upward biased estimates for the coefficient of the lagged dependent variable (Hsiao, 1986; Baltagi, 1995), and fixed effects estimator leads to a downward bias for the estimated parameter (Nickell, 1981). Hence, both OLS and FE approach would yield biased estimates also for the explanatory variables.

Arellano and Bond (1991) proposed using a Generalized Method of Moment (GMM) estimation to consider the problems pointed above. The dynamic equation is expressed in the first differences to remove firm specific effects, and the lagged values of the right-hand side variables are used as instruments in this first differenced equation (GMM-DIF). Then, it would be claimed that GMM-DIF provides consistently estimated parameters in the models by using instrumental variables for endogenous explanatory variables. However, taking the first differences removes most of the variation in the data if there is strong persistence in the time series. It implies that lagged values of explanatory variables would be weak instruments and thus large finite sample biases and imprecision can occur (Blundell and Bond, 1998; Blundell and Bond, 2000; Bond et al., 2001). In addition, the first difference GMM estimator is poorly behaved when the time dimension is small relative to its cross-section dimension. (Bond et al., 2001).

Blundell and Bond (1998) suggest using additional level moment conditions and obtaining system GMM estimation (GMM-SYS). GMM-SYS uses the lagged first-differences as instruments for equations in levels, in addition to the lagged levels as instruments for equations in the first differences. In this way, GMM-SYS uses all information available in the data (Bond, 2002). Then, GMM-SYS combines equations in levels with equations in first differences to gain asymptotic efficiency, and it has better asymptotic and finite sample properties compared to GMM-DIF (Bond et al., 2001, Blundell et al., 2000). Since the existence of strong persistent time series and short time dimension relative to cross-section units in our sample (i.e. large N and small T), we adopt GMM-SYS approach to estimate dynamic labor demand equation in this study. Note that the empirical issues considered in our estimation specifications are mainly based on Roodman (2006) and Roodman (2009).

Moreover, we take advantage of some strategies to improve the efficiency of GMM-SYS estimation. In this regard, we collapse the GMM instruments by creating one instrument for each variable and lag distance (rather than one for each time period, variable, and lag distance). Also, year dummies are included in all regressions to control for macroeconomic shocks. Including time specific effects in the regressions reduces the cross-sectional dependence in the error term as well. Moreover, our models include sector dummies in order to control industrial fixed effects. Arellano and Bond (1991) and Blundell and Bond (1998) points out that two-step standard errors are downward biased, but it is more efficient than those in one-step. Therefore, all GMM estimations in this study are conducted using a two-step efficient GMM technique to correct any non-spherical errors.

Furthermore, some usual econometric issues in the estimations are taken into consideration. First of all, Wald tests are conducted for overall joint significance of the explanatory variables and time and sector dummies. Also, Sargan and Hansen tests for over-identifying restrictions are performed to test the null hypothesis of adequate instruments. Arellano-Bond tests for the serial correlations are employed to test for existence of serial correlation in the first-differenced residuals. The null hypothesis is that the residuals are serially uncorrelated. If the null hypothesis for AR (1) is rejected, it implies that a dynamic specification is needed. If the null hypothesis for AR (2) cannot be rejected, it provides the evidence that there is no second-order serial correlation and the GMM estimator is consistent. Finally, we check the significant value of the coefficients of lagged employment for the persistence of employment time series. We then compare the results of OLS, FE, GMM-DIF and GMM-SYS with regard to estimated coefficients of lagged dependent variable for the consistency.

5. Estimation Results

In order to explore the effect of ICT capital on employment in Turkish manufacturing, we estimated the labor demand equation given in Equation (5) above by using OLS, FE, GMM-DIF and GMM-SYS. The baseline estimations were conducted by using all firms in the sample, and the results are reported in Table 7.

Before the discussion of the estimation results, some econometric issues are examined. First of all, we compare the results of OLS, FE, and GMM-DIF and GMM-SYS with regard to estimated coefficient of lagged dependent variables. GMM-DIF results do not satisfy the consistency of lagged coefficients with OLS and FE. FE estimates give lower values for the lagged dependent variable than those in OLS results, whereas GMM-SYS results provide higher values for the value of the estimated coefficient of the lagged dependent variable than those in FE estimates. Then, consistency of lagged coefficients among four methods supports to use GMM-SYS. We also check the persistence of employment time series. For all specifications in Table 7, the significant value of the lagged coefficients of employment confirms the persistence of its time series, favoring the adoption of GMM-SYS.

Moreover, we examine some diagnostic tests of results, which are performed to test the validity of model specification and baseline estimation results. All estimations include year and sector dummies but not reported to save space. Note that most of the coefficients of year and dummies are found to be significant. Wald test denotes a Wald test to test overall joint significance of the explanatory variables, which is asymptotically distributed as chi-squared with the degrees of freedom computed with respect to the number of restricted coefficients. According to Wald tests for overall joint significance of the explanatory variables and time and sector dummies, the null hypotheses of insignificant coefficients are always rejected.

Sargan and Hansen tests of over-identifying restrictions for the models in Table 7 presents strong evidence against the null hypothesis that the over-identifying restrictions are valid. However, there are two critical points for the reliability of those test results. First of all, Baum et al. (2003) indicates that the validity of inference on Sargan test diminishes if we use of heteroskedasticity-consistent or “robust” standard errors and statistics, as in our case. The other point is that it has been demonstrated that the Hansen test over-rejects the null in case of very large samples (Blundell and Bond, 1999; Roodman, 2006; 2009). Since both aspects exist in our estimations, we presume that there is no reliability Sargan and Hansen test results in our estimations.

According to Arellano-Bond test statistics for AR (1), the null hypothesis of no autocorrelation is rejected, hence it requires a dynamic specification. On the other hand, Arellano-Bond test statistics for AR (2) show that the consistency of the GMM estimators is supported, as there is no evidence of a second order serial correlation in the differenced residuals of the models. All in all, we rely on the GMM-SYS technique to investigate the effect of ICT capital on employment within the labor demand model.

Although we take the impact of ICT variables on employment into account, we also conduct the estimation by using only standard explanatory variables within labor demand equation (i.e.

without ICT) for consistency check of wage and output. Simple labor demand equation results for full sample are reported in Table A1 in appendix. Note that the simple labor demand equation includes total capital variable as well to avoid omitted variable bias.

Both the two models in Tables 7 provide statistically significant coefficients for the standard variables in the labor demand model for all estimation methods. The real wage coefficient shows negative and significant value, which is consistent with our expectation indicating a negative relationship between labor demand and wages. Firms' output has a positive effect on employment, which means that the expansion of production requires higher demand of labor.

The coefficient of ICT capital in model 1 is found to be positive and significant for OLS, FE, GMM-DIFF and GMM-SYS. Then, we can claim that the ICT capital has a positive effect on employment. When it comes to the discussion on resolving the impact of ICT capital as tangible and intangible, OLS results show that negative but not significant effect of tangible ICT capital on employment. However, the same impact turns out to be positive and significant in FE, GMM-DIFF and GMM-SYS estimates. On the other hand, the coefficient of intangible ICT capital is found to be positive and significant only in GMM-SYS. Therefore, all three ICT capital variables have significantly positive coefficients reflecting employment-enhancing effects.

The same specifications were used to estimate labor demand equation by splitting the sample in accordance with technological intensity to examine the impact of ICT capital on employment. The GMM-SYS estimation results by technological intensity are presented in Table 8. The lagged employment variable is positive and significant for all models and for all groups. In other words, time persistency in employment time series is satisfied and recommends using GMM-SYS as well. The results of Wald tests for overall joint significance of the explanatory variables and time and sector dummies show that the null hypotheses of insignificant coefficients are always rejected. According to Arellano-Bond test statistics for AR (1), the null hypothesis of no autocorrelation is rejected, so the need for a dynamic specification is satisfied. Furthermore, Arellano-Bond test statistics for AR (2) show that the consistency of the GMM estimators is supported, as there is no evidence of a second order serial correlation in the differenced residuals of the models.

For consistency check of wage and output, simple labor demand estimation results by technological intensity are reported in Table A2 in appendix as well. The real wage explanatory variable is significant and in line with the expected negative sign in all models in Table 8. The impact of the output variable is positive and significant on employment, indicating the higher production the higher demand of labor.

Although the coefficient of ICT capital in model 1 is found to be positive for all sectors, its impact is significant for low and medium technology sectors. We can say that ICT capital has a positive effect on employment in low and medium technology sectors. Regarding the discussion on separate effects of tangible ICT capital and intangible ICT capital (model 2), the coefficients of both are found to be positive and significant in low and medium technology sectors, again. Moreover, our results present the fact that tangible ICT capital has stronger employment generation impact than those for intangible ICT capital although the employment-enhancing effects are confirmed empirically for both types of ICT capital. Although we do not find statistically significant coefficients of ICT variables in high-tech sample, the hypothesis that ICT capital benefits job creation in high-tech sectors more may not be rejected. This is because very limited number of firms exist in our high-tech sample on the one hand, the coefficient estimates obtained for the high-tech sample is consistently higher than for both low and medium tech firms on the other hand.

Furthermore, to investigate the impact of ICT capital on employment for disaggregated industries, we estimate labor demand equation by splitting the sample into more detailed sub-sectors. We used intermediate aggregation definitions of NACE Rev.2, called intermediate SNA/ISIC aggregation A*38 (Eurostat, 2008). Specifically, this classification aggregates some of 24 manufacturing divisions (2-digit sectors) into 13 sub-sectors.

The GMM-SYS estimation results by sub-sectors are presented in Tables A3-A4 in appendix. When we check the coefficients of the lagged employment variable, they are found to be positive and significant for all models and sectors, except few ones. In other words, time persistency in employment time series is satisfied, favoring the adoption of GMM-SYS again. Moreover, the real wage explanatory variables are significant and in line with the expected negative sign in both two models Tables A3-A4 in appendix. The impact of the output variable is positive and significant on employment. In other words, the expansion of production requires higher demand of labor. Then, we can claim that all standard variables in labor demand equation have expected sign and statistically significant coefficients for all sub-sector samples.

In order to examine the impact of ICT capital variables, we constructed a summary table (Table 9) for both two models and all sub-sectors. Table 9 represents the coefficient estimates of ICT capital variables in question with significance levels. The coefficient of ICT capital variable is found to be positive and significant for the food products, beverages and tobacco (10 to 12), chemicals and chemical products (20), rubber and plastics products, and other non-metallic mineral products (22+23), electrical equipment (27), machinery and equipment n.e.c. (28), and transport equipment (29+30) sectors. Then, our results indicate that ICT has an employment-enhancing effect for half of the sub-sectors reported in Table 9. Also, separate impacts of ICT capital as tangible and intangible are found to be positive and significant for the sub-sectors that have positive (total) ICT effect. Moreover, one can see that tangible ICT capital has larger coefficient for almost all sub-sectors.

Figure 2, alternatively, provides the coefficient estimates of ICT capital variables with 95 % confidence intervals by sub-sectors. One can clearly see that our results support the employment-enhancing effect of ICT. In other words, it is more prominent that coefficient estimates of variables in question are located in positive region.

6. Robustness Check

In order to control the validity of our estimation results, we have conducted several regressions for robustness check.

We have used two-step efficient GMM techniques to correct any non-spherical errors. Since two-step standard errors are downward biased, we conducted all GMM estimations using one-step, alternatively. Corresponding standard errors are slightly larger than two-step, but all variables in question remain significant and have the same effects leaving our results unaltered.

As it is discussed in empirical strategy section and estimation results above, we presume that there is no reliability of Sargan and Hansen test results in our estimations due to the sensitivity of those in the case of using robust standard errors, and very large samples. For the consistency check, we run same GMM regressions by using random sub-samples comprising very small parts (5 %, 10 %, or 20 %) of the original data. The null hypothesis of adequate instruments of Sargan and/or Hansen tests was not rejected.

Robust standard errors in all regressions for full sample and the sub-samples of technological intensity are clustered at 2-digit sector level. Alternatively, we used robust-clustered standard errors at 3-digit level, 4-digit level, and firm-level, respectively. As clustering level increases to more disaggregated level, corresponding standard errors become slightly lower and lower.

Therefore, our results are unaffected. This is because our models already correct standard errors at more aggregated level (2-digit), which have higher standard errors in this context.

Since capital stock series is not available in the data, capital stock series are constructed by using the perpetual inventory method in this study. As it is discussed in Data section above, we have used 7.5% as a depreciation rate for tangible non-ICT capital stock, and 25% for intangible non-ICT capital stock, tangible ICT capital stock, intangible ICT capital stock, separately. Instead of 7.5 % and 25 %, we take alternative depreciation rates for tangible non-ICT capital stock as 5 % and 10 %, whereas for other capital stock series as 20 % and 30 %. The regressions with capital stock variables that constructed by alternative depreciation rates leave our main results intact.

We estimated all models by introducing size class dummy variables in order to control firm size. We used three size group according to EU definition, small (10-49), medium (50-249), and large (>249). Since our sample includes the enterprises with 20 or more employees, our small firm size is defined for the firms with 20-49 employees. All labor demand estimation results with size class dummies are reported in Tables A5-A8 in appendix for full sample, by technological intensity, and sub-sectors, respectively. The coefficients of the dummy variables for medium- and large-sized firms turned out to be positive and statistically significant for almost all regressions. Note that the regressions with size class controls do not distort the effects of other variables in the models, and produce results in line with the main findings.

Instead of ICT capital stock variables, we used ICT capital share out of total capital to proxy ICT use in labor demand equation. Tables A9-A11 in appendix show that similar effects leave our results unaltered.

In order to check the validity of employment-enhancing impact of ICT for capital-intensive firms, first we simply calculate (log) ratio of real capital to labor for each firm-year observation. Then, we classify the firms into higher capital intensive and lower capital intensive by setting manufacturing industry median value of the ratio as the threshold. It is reported in Table A12 in appendix that our main models do not change according to capital intensity.

Finally, we estimate labor demand equation by splitting the sample into 2-digit sectors (NACE Rev. 2) to investigate the impact of ICT capital on employment at a more disaggregated sector level. The GMM-SYS estimation results by 2-digit sectors and for different technological intensive industries are presented in Tables A13-A14 in appendix. Also, Figures A1-A3 provides coefficient estimates of ICT variables with 95 % confidence intervals for corresponding estimations. By skipping the discussion of each estimate, we point out some findings as follows: Employment creation impact of ICT is confirmed for some 2-digit sectors whereas that impact is not significant for some other sectors. The mixed picture may be due to the small number firms/observations and low degrees of freedom problem for some sectors.

Our main results by for different technology intensive industries above show that the strongest job-creating impact of ICT exists in medium tech firms. This finding is consistent with the results by 2-digit sectors. Note that we used technological intensity classification of Eurostat (Eurostat, 2015) as three groups: low, medium, and high tech. Indeed, medium technology intensity group can be also divided into two, medium-low and medium-high, according to Eurostat (2015). In this regard, medium-high technology intensity sectors are chemicals and chemical products (20), electrical equipment (27), machinery and equipment n.e.c. (28), motor vehicles, trailers and semi-trailers (29), and other transport equipment (30). Figure A1 exhibits that ICT has employment-enhancing impact in almost all medium-high technology intensity sectors. Moreover, we can claim that employment-enhancing impact of medium technology sectors sources from medium-high technology sectors. This is because there is no or few finding for the same impact in medium-low technology sectors in Figures A1-A3. This finding also supports our argument that insignificant finding of employment creation impact of ICT in high tech sector should be due to insufficient number of observation/firms in this group.

These figures also underline the heterogeneity of detailed sectors since the distinct sectors have own peculiarities in terms of compensation and substitution mechanisms.

7. Concluding Remarks

There are two main theoretical approaches in the literature on the impact of technology, using ICT indicators as proxy, on employment. Substitution effect asserts that labor saving effect of ICT dominates, and employment destruction emerges as traditional industries improve their technology because new technologies require less labor. However, compensation mechanism claims that labor saving effect of technological progress may be compensated via some mechanism by market oriented indirect effects, underlining technological change lead to employment generation in the long run. There exists a sizable literature on the impact of technology on employment. However, since both compensation mechanisms and substitution effect are supported in empirical studies, there is no consensus on the direction of employment creation/destruction effect of ICT.

This study is said to be the first attempt in exploring the impact of ICT on employment generation in Turkish manufacturing at the firm level by using labor demand estimation from a dynamic perspective. The analysis is based on firm level data obtained from Turkish Statistical Institute (TurkStat) and covers the period from 2003 to 2013. The data used in the analysis includes all firms employing 20 or more employees in Turkish manufacturing industry.

For all firms' sample, our results support that the impact of ICT on employment is positive for all specifications. We, therefore, conclude that ICT has an employment-enhancing effect in Turkish manufacturing. Our data fits that the compensation mechanism is confirmed for Turkish manufacturing industry. Similar results are valid for low and medium technology intensive manufacturing industries. Moreover, our results show that tangible ICT capital has a stronger employment generation impact than that of intangible ICT capital in medium- and low-tech industries. However, none of our models supports significantly employment creation impact of ICT for high-tech sectors. This might be due to the fact that sample size is relatively small in high-tech sectors. One other reason might be the fact that the use of ICT in these industries is already very high. Therefore, the marginal impact of ICT use may not be significant in high technology intensive industries of manufacturing.

We, in this study, also estimated labor demand equations by using alternative models for some detailed sectors. Our results indicate that the employment creation impact of ICT, compensation mechanism, is confirmed for almost all aggregate samples. This impact is preserved in most sub-sectors. Furthermore, our findings support that employment-enhancing impact of ICT in medium technology intensive industries is derived from medium-high technology sectors. On the other hand, that impact is not significant for some other sectors especially in the estimations by 2-digit sectors. Therefore, sectoral heterogeneity is valid for the impact of ICT on employment.

We are aware that this study has own restrictions and limitations. Therefore, some important issues should be addressed for further studies: First of all, in terms of both compensation mechanism and substitution mechanism, the employment impact of ICT may depend on innovation type, i.e. product innovation and process innovation. Although most of the studies in the literature underlined that product innovation is likely to be more labor-friendly while process innovation has labor-saving impacts, trying to empirically discover the employment-ICT nexus in this context merits for another research. Second, the heterogeneity of industries according to ICT-producing and ICT-using positions can matter for the impact of ICT on employment. The last but not the least, a comprehensive research on the employment creation or destruction effects of ICT by using datasets at different aggregation levels (macro-sector-firm) at the same time may disentangle elusive impact, as suggested by Sabadash (2013) and Vivarelli (2014).

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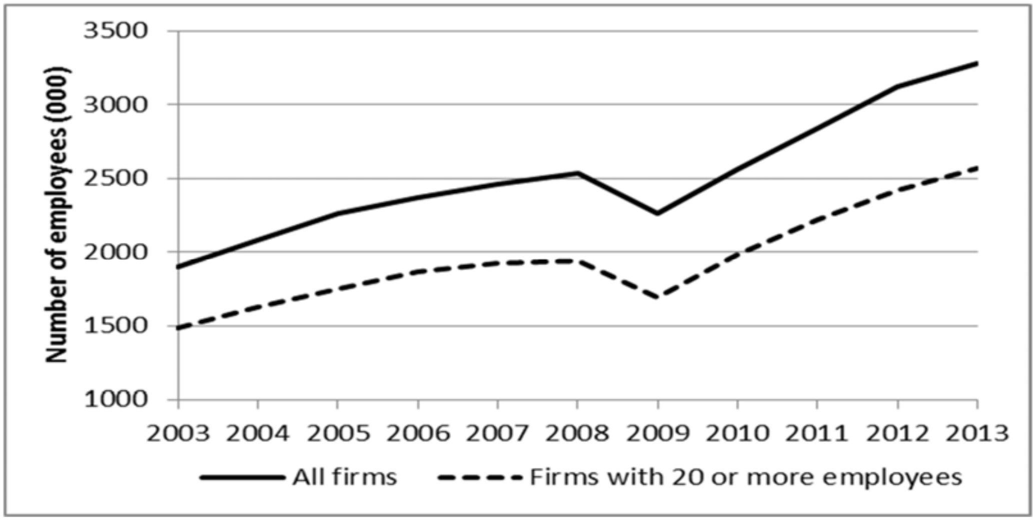
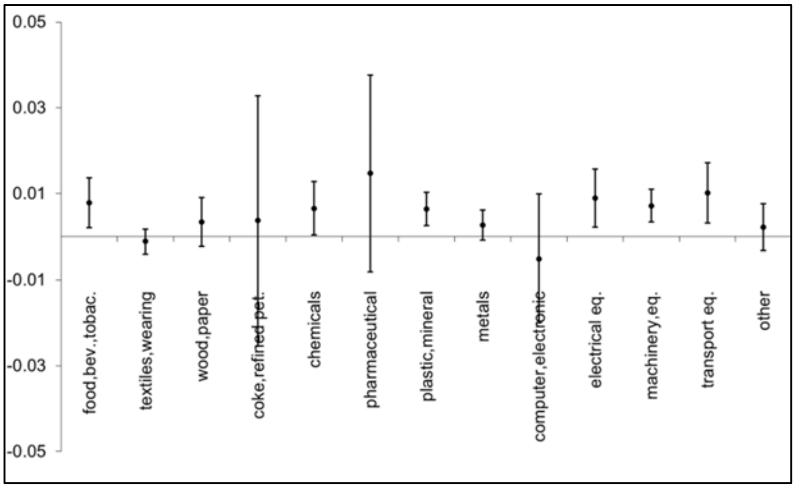
Figure 1: Evolution of Employment in Turkish Manufacturing Industry



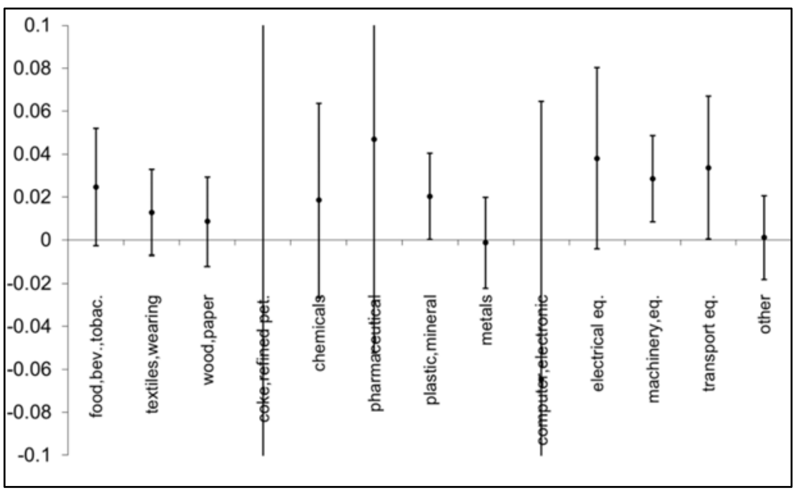
Source: Authors' calculation from TurkStat Annual Industry and Service Statistics

Figure 2: Coefficient Estimates of ICT Capital Variables with 95 % Confidence Intervals By Sub-Sectors

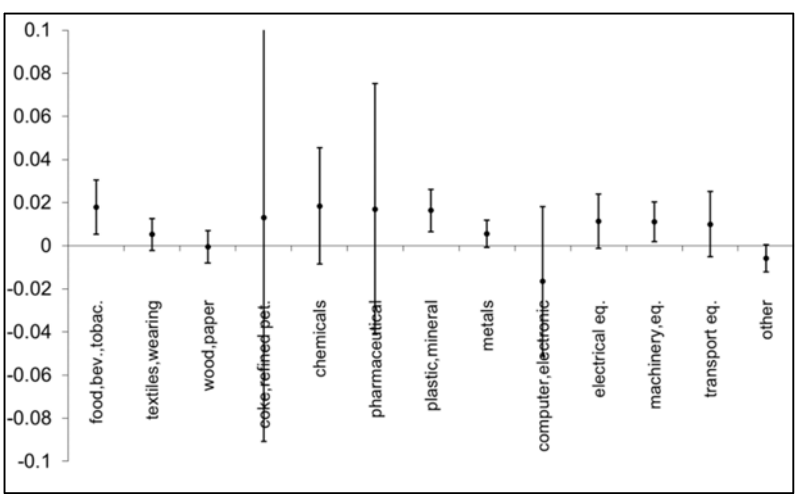
ICT capital



Tangible ICT capital



Intangible ICT capital



Note: See Table A3-A4 in appendix for full estimation results by sub-sectors.

Table 1: Manufacturing Industry in Turkish Economy, 2003-2013

Year	Number of firms	Share in Total Eonomy (%) Employment	Share in Total Eonomy (%) Output	Growth rate (%) Employment	Growth rate (%) Output
2003	236275	17.3	19.8	-1.8	8.3
2004	281029	19.1	19.5	2.1	11.7
2005	302459	19.9	19.4	6.7	8.2
2006	309841	19.9	19.3	1.8	8.5
2007	316596	19.7	18.6	0.5	5.6
2008	321652	20.0	17.8	3.6	-0.1
2009	320815	18.6	16.6	-6.8	-7.3
2010	299928	18.7	17.4	6.8	13.8
2011	333288	18.1	18.2	3.6	10.0
2012	336893	17.8	17.4	1.2	1.7
2013	340438	18.1	17.3	4.8	3.7

Source: Own elaborations from TurkStat National Accounts, Labor Force Statistics.

Table 2: Firms in Our Sample: Manufacturing Enterprises With 20 or More Employees, 2003-2013

Year	Number of firms	Share in Total (%) Low-tech	Share in Total (%) Medium-tech	Share in Total (%) High-tech
2003	14067	60.9	37.7	1.4
2004	16372	54.3	44.3	1.4
2005	18910	52.8	45.9	1.3
2006	19984	52.6	46.1	1.3
2007	19513	53.5	45.1	1.4
2008	19036	52.3	46.2	1.5
2009	16442	50.3	48.0	1.6
2010	21748	52.1	46.3	1.6
2011	24588	51.1	47.5	1.4
2012	27075	53.0	45.7	1.3
2013	28086	52.4	46.1	1.4

Source: Authors' calculation from TurkStat Annual Industry and Service Statistics.

Table 3: Our sample's Share in Total Manufacturing (%)

Year	Employment	Output	Value added
2003	78.2	88.3	88.3
2004	77.9	89.1	89.8
2005	77.2	88.1	88.4
2006	78.6	89.2	91.0
2007	78.1	88.4	90.4
2008	76.4	88.4	89.8
2009	74.7	86.5	88.9
2010	77.4	88.5	89.6
2011	78.1	89.9	91.4
2012	77.4	90.2	90.2
2013	78.3	89.7	91.2

Source: Authors' calculation from TurkStat Annual Industry and Service Statistics

Table 4: Distribution of Firms by 2 Digit NACE Rev.2 (%)

Code	Sector Name	Firms	Employment	Output	Value added
10	Manufacture of food products	10.1	10.6	13.5	10.3
11	Manufacture of beverages	0.5	0.5	1.0	1.3
12	Manufacture of tobacco products	0.1	0.8	0.9	1.3
13	Manufacture of textiles	11.3	14.9	9.2	9.7
14	Manufacture of wearing apparel	17.3	15.7	6.7	6.8
15	Manufacture of leather and related products	2.4	1.5	0.8	0.8
16	Manufacture of wood and of products of wood and cork, except furniture;	1.6	1.0	1.0	1.1
17	Manufacture of paper and paper products	1.9	1.7	1.9	1.9
18	Printing and reproduction of recorded media	1.6	0.9	0.6	0.8
19	Manufacture of coke and refined petroleum products	0.3	0.4	5.5	2.4
20	Manufacture of chemicals and chemical products	2.4	2.1	4.6	4.4
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations	0.5	1.4	1.9	2.8
22	Manufacture of rubber and plastic products	5.9	4.5	4.5	4.9
23	Manufacture of other non-metallic mineral products	7.3	7.2	6.0	8.3
24	Manufacture of basic metals	3.3	4.6	12.0	8.9
25	Manufacture of fabricated metal products, except machinery and equipment	9.1	8.6	5.1	8.2
26	Manufacture of computer, electronic and optical products	0.9	1.3	2.0	1.9
27	Manufacture of electrical equipment	3.2	4.3	5.4	5.7
28	Manufacture of machinery and equipment n.e.c.	7.0	5.0	3.6	4.7
29	Manufacture of motor vehicles, trailers and semi-trailers	3.4	6.0	9.4	8.9
30	Manufacture of other transport equipment	1.1	1.2	1.0	1.4
31	Manufacture of furniture	4.4	3.2	1.5	1.7
32	Other manufacturing	2.2	1.3	1.3	1.0
33	Repair and installation of machinery and equipment	2.1	1.1	0.4	0.8

Source: Authors' calculation from TurkStat Annual Industry and Service Statistics.

Table 5: Distribution of Firms by Technological Intensity (%)

	Firms	Employment	Output	Value added
Low technology	53.5	52.4	38.5	36.7
Medium technology	45.0	44.9	57.6	58.6
High technology	1.5	2.8	4.0	4.7

Source: Authors' calculation from TurkStat Annual Industry and Service Statistics

Table 6: Proportion of ICT Use and ICT Capital (%)

		Share in Total Capital		
Year	ICT using firms	ICT	Tangible ICT	Intangible ICT
2003	67.5	48.3	35.6	12.7
2004	67.1	48.5	35.9	12.6
2005	77.8	48.0	36.1	11.9
2006	79.3	47.7	36.3	11.4
2007	80.4	47.2	35.8	11.5
2008	78.2	47.0	35.8	11.3
2009	82.1	46.4	35.2	11.3
2010	80.9	46.1	35.7	10.3
2011	76.4	46.4	36.6	9.8
2012	76.0	46.4	36.7	9.7
2013	70.0	46.8	37.0	9.8

Source: Authors' calculation from TurkStat Annual Industry and Service Statistics.

Table 7: Labor Demand Estimation Results: Full Sample

	(1)				(2)			
	OLS	**FE**	**GMM-D**	**GMM-S**	**OLS**	**FE**	**GMM-D**	**GMM-S**
Employment_{it-1}	0.781***	0.394***	0.001	0.554***	0.789***	0.439***	0.109***	0.536***
	[0.003]	[0.006]	[0.024]	[0.027]	[0.004]	[0.008]	[0.030]	[0.037]
Wage_{it}	-0.148***	-0.232***	-0.211***	-0.201***	-0.153***	-0.242***	-0.219***	-0.213***
	[0.004]	[0.011]	[0.011]	[0.007]	[0.004]	[0.014]	[0.016]	[0.010]
Output_{it}	0.182***	0.402***	0.379***	0.290***	0.181***	0.376***	0.351***	0.298***
	[0.002]	[0.005]	[0.006]	[0.011]	[0.003]	[0.007]	[0.008]	[0.016]
NonICT_{it}	0.001***	0.003***	0.006***	0.002***	0.002***	0.002	0.004***	0.005***
	[0.000]	[0.001]	[0.001]	[0.000]	[0.000]	[0.001]	[0.001]	[0.001]
ICT_{it}	0.001**	0.008***	0.013***	0.006***				
	[0.000]	[0.001]	[0.001]	[0.001]				
ICTtang_{it}					-0.001	0.021***	0.025***	0.024***
					[0.001]	[0.003]	[0.003]	[0.004]
ICTintang_{it}					0.001	-0.002*	0.001	0.009***
					[0.001]	[0.001]	[0.001]	[0.002]
Constant	-0.647***	-1.783***		-1.088***	-0.633***	-1.578***		-1.345***
	[0.028]	[0.098]		[0.084]	[0.033]	[0.129]		[0.142]
Observations	150075	150075	117708	150075	74539	74539	61000	74539
Firms		30861	25278	30861		12776	11019	12776
R-squared	0.883	0.517			0.913	0.563		
Wald test			12635.9	146455.0			372451.5	100273.4
Sargan			(0.059)	(0.000)			(0.769)	(0.000)
Hansen			(0.066)	(0.000)			(0.776)	(0.000)
AR(1)			(0.000)	(0.000)			(0.000)	(0.000)
AR(2)			(0.000)	(0.117)			(0.003)	(0.768)

Notes: All models include year and sector dummies (2-digit) but not reported to save space. Both GMM, difference (GMM-D) and system (GMM-S), were all conducted with two-step efficient GMM. Robust standard errors clustered at sector level are reported in brackets *** p<0.01, ** p<0.05, * p<0.1. p-values for the tests (Sargan, Hansen, AR) are in parentheses.

Table 8: Labor Demand Estimation by Technological Intensity (GMM-SYS estimates)

	Low-tech		**Medium-tech**		**High-tech**	
Employment_{it-1}	0.744***	0.676***	0.423***	0.477***	0.591***	0.570***
	[0.033]	[0.051]	[0.039]	[0.052]	[0.137]	[0.176]
Wage_{it}	-0.192***	-0.225***	-0.211***	-0.200***	-0.272***	-0.291***
	[0.014]	[0.023]	[0.008]	[0.010]	[0.039]	[0.042]
Output_{it}	0.204***	0.235***	0.358***	0.332***	0.304***	0.304***
	[0.013]	[0.022]	[0.017]	[0.023]	[0.067]	[0.075]
NonICT_{it}	0.001	0.003***	0.003***	0.004***	0.004	0.003
	[0.001]	[0.001]	[0.001]	[0.001]	[0.004]	[0.005]
ICT_{it}	0.002*		0.008***		0.009	
	[0.001]		[0.001]		[0.006]	
ICTtang_{it}		0.013**		0.020***		0.043
		[0.006]		[0.006]		[0.034]
ICTintang_{it}		0.004*		0.011***		0.011
		[0.002]		[0.002]		[0.010]
Constant	-0.459***	-0.601***	-1.650***	-1.852***	-0.861*	-1.214*
	[0.130]	[0.214]	[0.175]	[0.208]	[0.445]	[0.698]
Observations	78448	37458	69361	35407	2266	1674
Firms	16431	6674	14413	6019	502	324
Wald test	107363.0	60883.8	57174.1	46695.6	6547.4	6540.8
Sargan	(0.000)	(0.000)	(0.000)	(0.000)	(0.027)	(0.011)
Hansen	(0.000)	(0.000)	(0.000)	(0.000)	(0.316)	(0.295)
AR(1)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.007)
AR(2)	(0.281)	(0.616)	(0.496)	(0.913)	(0.548)	(0.544)

Notes: All models include year and sector dummies (2-digit) but not reported to save space. All estimations were conducted with two-step efficient GMM. Robust standard errors clustered at sector level are reported in brackets *** p<0.01, ** p<0.05, * p<0.1. p-values for the tests (Sargan, Hansen, AR) are in parentheses.

Table 9: Coefficient Estimates of ICT Capital Variables by Sub-Sectors

A*38 codes	Divisions	Nace Rev.2 Industries	ICT	ICTtang	ICTintang
CA	10 to 12	Food products, beverages and tobacco	0.008***	0.025*	0.018***
CB	13 to 15	Textiles, wearing apparel, leather and related products	-0.001	0.013	0.005
CC	16 to 18	Wood and paper products; printing and reproduction of recorded media	0.003	0.009	-0.001
CD	19	Coke and refined petroleum products	0.004	-0.190	0.013
CE	20	Chemicals and chemical products	0.007**	0.019	0.019
CF	21	Basic pharmaceutical products and pharmaceutical preparations	0.015	0.047	0.017
CG	22+23	Rubber and plastics products, and other non-metallic mineral products	0.006***	0.020**	0.016***
CH	24+25	Basic metals and fabricated metal products, except machinery and equipment	0.003	-0.001	0.006*
CI	26	Computer, electronic and optical products	-0.005	-0.065	-0.017
CJ	27	Electrical equipment	0.009***	0.038*	0.011*
CK	28	Machinery and equipment n.e.c.	0.007***	0.029***	0.011**
CL	29+30	Transport equipment	0.010***	0.034**	0.010
CM	31 to 33	Other manufacturing; repair and installation of machinery and equipment	0.002	0.001	-0.006*

Note: See Table A3-A4 in appendix for full estimation results by sub-sectors.

Appendix

Table A1: Simple Labor Demand Estimation Results: Full Sample

	(1)				(2)			
	OLS	FE	GMM-D	GMM-S	OLS	FE	GMM-D	GMM-S
$Employment_{it-1}$	0.770***	0.384***	-0.117***	0.478***	0.781***	0.394***	0.002	0.545***
	[0.002]	[0.005]	[0.024]	[0.025]	[0.003]	[0.006]	[0.024]	[0.027]
$Wage_{it}$	-0.138***	-0.229***	-0.198***	-0.183***	-0.148***	-0.232***	-0.211***	-0.200***
	[0.004]	[0.010]	[0.010]	[0.006]	[0.004]	[0.011]	[0.011]	[0.007]
$Output_{it}$	0.189***	0.423***	0.407***	0.338***	0.182***	0.402***	0.379***	0.294***
	[0.002]	[0.005]	[0.006]	[0.012]	[0.002]	[0.005]	[0.006]	[0.011]
$TotCAP_{it}$					0.001***	0.005***	0.009***	0.004***
					[0.000]	[0.001]	[0.001]	[0.001]
Constant	-0.788***	-1.871***		-1.563***	-0.646***	-1.792***		-1.125***
	[0.026]	[0.092]		[0.094]	[0.028]	[0.098]		[0.086]
Observations	185180	185180	139872	185180	150075	150075	117708	150075
Firms		43567	32296	43567		30861	25278	30861
R-squared	0.874	0.513			0.884	0.517		
Wald test			10606.2	133631.2			12707.6	142393.3
Sargan			(0.005)	(0.000)			(0.060)	(0.000)
Hansen			(0.006)	(0.000)			(0.068)	(0.000)
AR(1)			(0.685)	(0.000)			(0.000)	(0.000)
AR(2)			(0.009)	(0.610)			(0.000)	(0.131)

Notes: All models include year and sector dummies (2-digit) but not reported to save space. Both GMM, difference (GMM-D) and system (GMM-S), were all conducted with two-step efficient GMM. Robust standard errors clustered at sector level are reported in brackets *** p<0.01, ** p<0.05, * p<0.1. p-values for the tests (Sargan, Hansen, AR) are in parentheses.

Table A2: Simple Labor Demand Estimation by Technological Intensity (GMM-SYS estimates)

	Low-tech		Medium-tech		High-tech	
$Employment_{it-1}$	0.631***	0.734***	0.439***	0.421***	0.578***	0.592***
	[0.033]	[0.033]	[0.033]	[0.039]	[0.092]	[0.135]
$Wage_{it}$	-0.181***	-0.193***	-0.191***	-0.210***	-0.244***	-0.270***
	[0.013]	[0.014]	[0.007]	[0.008]	[0.029]	[0.037]
$Output_{it}$	0.258***	0.208***	0.366***	0.360***	0.334***	0.304***
	[0.015]	[0.013]	[0.016]	[0.017]	[0.056]	[0.067]
$TotCAP_{it}$		0.001		0.005***		0.006
		[0.001]		[0.001]		[0.004]
Constant	-0.937***	-0.478***	-1.763***	-1.687***	-1.454***	-0.878*
	[0.140]	[0.132]	[0.173]	[0.177]	[0.402]	[0.449]
Observations	98494	78448	84001	69361	2685	2266
Firms	23992	16431	19539	14413	638	502
Wald test	82267.4	103244.2	65967.2	56498.2	5907.1	6464.8
Sargan	(0.000)	(0.000)	(0.000)	(0.000)	(0.052)	(0.030)
Hansen	(0.000)	(0.000)	(0.000)	(0.000)	(0.445)	(0.329)
AR(1)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AR(2)	(0.382)	(0.284)	(0.798)	(0.512)	(0.546)	(0.543)

Notes: All models include year and sector dummies (2-digit) but not reported to save space. All estimations were conducted with two-step efficient GMM. Robust standard errors clustered at sector level are reported in brackets *** p<0.01, ** p<0.05, * p<0.1. p-values for the tests (Sargan, Hansen, AR) are in parentheses.

Table A3: GMM-SYS Estimates by Sub-Sectors: Model 1

	(10t12)	**(13t15)**	**(16t18)**	**(19)**	**(20)**	**(21)**	**(22a23)**	**(24a25)**	**(26)**	**(27)**	**(28)**	**(29a30)**	**(31t33)**
$Employment_{it-1}$	0.690***	0.760***	0.451***	0.843**	0.574***	0.277	0.459***	0.632***	0.851***	0.394***	0.432***	0.432***	0.559***
	[0.069]	[0.044]	[0.144]	[0.351]	[0.150]	[0.381]	[0.060]	[0.063]	[0.132]	[0.120]	[0.076]	[0.108]	[0.091]
$Wage_{it}$	-0.187***	-0.192***	-0.122***	-0.131	-0.192***	-0.347***	-0.260***	-0.177***	-0.227***	-0.144***	-0.207***	-0.203***	-0.277***
	[0.015]	[0.020]	[0.043]	[0.120]	[0.023]	[0.097]	[0.016]	[0.014]	[0.044]	[0.024]	[0.015]	[0.032]	[0.027]
$Output_{it}$	0.172***	0.211***	0.337***	0.169	0.265***	0.481**	0.335***	0.254***	0.202***	0.380***	0.374***	0.364***	0.310***
	[0.023]	[0.019]	[0.063]	[0.107]	[0.070]	[0.221]	[0.025]	[0.027]	[0.058]	[0.057]	[0.034]	[0.051]	[0.032]
$NonICT_{it}$	0.009***	-0.003***	0.001	-0.007*	0.009**	0.022	0.001	0.001	-0.003	0.001	0.004***	0.005**	-0.000
	[0.002]	[0.001]	[0.001]	[0.004]	[0.004]	[0.018]	[0.001]	[0.001]	[0.003]	[0.002]	[0.001]	[0.002]	[0.002]
ICT_{it}	0.008***	-0.001	0.003	0.004	0.007**	0.015	0.006***	0.003	-0.005	0.009***	0.007***	0.010***	0.002
	[0.003]	[0.001]	[0.003]	[0.015]	[0.003]	[0.012]	[0.002]	[0.002]	[0.008]	[0.003]	[0.002]	[0.004]	[0.003]
Constant	-0.077	-0.436**	-2.015***	-0.907	-1.095*	-2.065	-0.734***	-0.903***	-0.190	-2.315***	-1.817***	-1.721***	-0.437***
	[0.154]	[0.181]	[0.460]	[1.501]	[0.563]	[1.724]	[0.151]	[0.191]	[0.389]	[0.498]	[0.242]	[0.419]	[0.157]
Observations	16803	44442	7832	438	4235	827	20701	18076	1439	5283	11370	7093	11536
Firms	3383	9396	1691	120	911	154	4315	4085	348	1151	2600	1481	2909

Table A4: GMM-SYS Estimates by Sub-Sectors: Model 2

	(10t12)	**(13t15)**	**(16t18)**	**(19)**	**(20)**	**(21)**	**(22a23)**	**(24a25)**	**(26)**	**(27)**	**(28)**	**(29a30)**	**(31t33)**
$Employment_{it-1}$	0.543***	0.611***	0.761***	1.996**	0.440	0.286	0.405***	0.682***	1.053***	0.429**	0.460***	0.442***	0.803***
	[0.110]	[0.082]	[0.113]	[0.793]	[0.357]	[0.368]	[0.088]	[0.087]	[0.278]	[0.171]	[0.093]	[0.136]	[0.076]
$Wage_{it}$	-0.240***	-0.235***	-0.099**	-0.489**	-0.203***	-0.366***	-0.251***	-0.168***	-0.245***	-0.120***	-0.210***	-0.258***	-0.172***
	[0.032]	[0.018]	[0.045]	[0.242]	[0.042]	[0.099]	[0.022]	[0.017]	[0.059]	[0.027]	[0.019]	[0.033]	[0.026]
$Output_{it}$	0.246***	0.279***	0.182***	-0.168	0.315**	0.489**	0.367***	0.233***	0.162*	0.350***	0.355***	0.365***	0.181***
	[0.044]	[0.035]	[0.055]	[0.204]	[0.155]	[0.216]	[0.039]	[0.037]	[0.089]	[0.078]	[0.043]	[0.067]	[0.031]
$NonICT_{it}$	0.017***	0.001	0.002	-0.034	0.013	0.015	0.001	0.003*	-0.005	0.002	0.004**	0.008**	-0.001
	[0.004]	[0.001]	[0.002]	[0.042]	[0.010]	[0.021]	[0.002]	[0.002]	[0.005]	[0.003]	[0.002]	[0.004]	[0.002]
$ICTtang_{it}$	0.025*	0.013	0.009	-0.190	0.019	0.047	0.020**	-0.001	-0.065	0.038*	0.029***	0.034**	0.001
	[0.014]	[0.010]	[0.011]	[0.206]	[0.023]	[0.051]	[0.010]	[0.011]	[0.066]	[0.022]	[0.010]	[0.017]	[0.010]
$ICTintang_{it}$	0.018***	0.005	-0.000	0.013	0.019	0.017	0.016***	0.006*	-0.017	0.011*	0.011**	0.010	-0.006*
	[0.006]	[0.004]	[0.004]	[0.053]	[0.014]	[0.030]	[0.005]	[0.003]	[0.018]	[0.006]	[0.005]	[0.008]	[0.003]
Constant	-0.659**	-0.750**	-1.119**	6.361	-1.606	-2.391	-1.370***	-0.878***	0.739	-2.647***	-1.938***	-1.655***	-0.322
	[0.300]	[0.340]	[0.447]	[4.780]	[1.359]	[2.070]	[0.273]	[0.312]	[1.027]	[0.854]	[0.367]	[0.557]	[0.215]
Observations	6965	22238	4015	191	2499	659	9391	9205	1015	3142	6097	4128	4994
Firms	1100	4118	707	43	437	107	1575	1681	217	593	1175	720	1103

Table A5: Labor Demand Estimation with Size Class Dummies: Full Sample

	(1)				(2)			
	OLS	**FE**	**GMM-D**	**GMM-S**	**OLS**	**FE**	**GMM-D**	**GMM-S**
$Employment_{it-1}$	0.609***	0.304***	-0.080***	0.351***	0.610***	0.339***	0.011	0.291***
	[0.004]	[0.005]	[0.022]	[0.036]	[0.005]	[0.007]	[0.028]	[0.049]
$Wage_{it}$	-0.120***	-0.192***	-0.172***	-0.151***	-0.122***	-0.198***	-0.177***	-0.155***
	[0.003]	[0.009]	[0.010]	[0.006]	[0.004]	[0.012]	[0.013]	[0.008]
$Output_{it}$	0.154***	0.347***	0.340***	0.233***	0.152***	0.316***	0.308***	0.241***
	[0.002]	[0.005]	[0.005]	[0.009]	[0.003]	[0.007]	[0.008]	[0.012]
$NonICT_{it}$	0.000	0.000	0.005***	0.001***	0.001***	0.000	0.003***	0.004***
	[0.000]	[0.001]	[0.001]	[0.000]	[0.000]	[0.001]	[0.001]	[0.001]
ICT_{it}	-0.001***	0.005***	0.011***	0.003***				
	[0.000]	[0.001]	[0.001]	[0.001]				
$ICTtang_{it}$					-0.003***	0.014***	0.023***	0.018***
					[0.001]	[0.002]	[0.002]	[0.004]
$ICTintang_{it}$					-0.000	-0.003**	0.001	0.008***
					[0.001]	[0.001]	[0.001]	[0.001]
Medium-sized	0.372***	0.381***	0.335***	0.479***	0.361***	0.378***	0.334***	0.501***
	[0.003]	[0.005]	[0.005]	[0.019]	[0.005]	[0.007]	[0.007]	[0.025]
Large-sized	0.756***	0.771***	0.688***	1.107***	0.754***	0.753***	0.690***	1.171***
	[0.008]	[0.012]	[0.013]	[0.057]	[0.011]	[0.015]	[0.016]	[0.071]
Constant	0.049*	-1.019***		-0.039	0.121***	-0.742***		-0.169**
	[0.026]	[0.088]		[0.053]	[0.030]	[0.113]		[0.082]
Observations	150075	150075	117708	150075	74539	74539	61000	74539
Firms		30861	25278	30861	12776	11019	12776	
R-squared	0.901	0.590			0.928	0.639		
Wald test			16925.5	192719.5			46960.4	111070.9
Sargan			(0.005)	(0.000)			(0.312)	(0.000)
Hansen			(0.006)	(0.000)			(0.331)	(0.000)
AR(1)			(0.000)	(0.000)			(0.000)	(0.000)
AR(2)			(0.000)	(0.103)			(0.000)	(0.099)

Notes: All models include year and sector dummies (2-digit) but not reported to save space. Both GMM, difference (GMM-D) and system (GMM-S), were all conducted with two-step efficient GMM. Robust standard errors clustered at sector level are reported in brackets *** p<0.01, ** p<0.05, * p<0.1. p-values for the tests (Sargan, Hansen, AR) are in parentheses.

Table A6: Labor Demand Estimation with Size Class Dummies by Technological Intensity (GMM-SYS estimates)

	Low-tech		Medium-tech		High-tech	
Employment$_{it-1}$	0.594***	0.397***	0.169***	0.263***	0.471***	0.450***
	[0.047]	[0.071]	[0.054]	[0.065]	[0.129]	[0.171]
Wage$_{it}$	-0.149***	-0.159***	-0.165***	-0.152***	-0.219***	-0.229***
	[0.012]	[0.017]	[0.007]	[0.007]	[0.026]	[0.029]
Output$_{it}$	0.163***	0.198***	0.306***	0.270***	0.239***	0.239***
	[0.010]	[0.016]	[0.015]	[0.018]	[0.041]	[0.046]
NonICT$_{it}$	-0.000	0.003***	0.002***	0.003***	0.002	-0.001
	[0.001]	[0.001]	[0.001]	[0.001]	[0.003]	[0.004]
ICT$_{it}$	-0.001		0.006***		0.005	
	[0.001]		[0.001]		[0.004]	
ICTtang$_{it}$		0.013**		0.013***		0.029
		[0.006]		[0.005]		[0.024]
ICTintang$_{it}$		0.005**		0.008***		0.007
		[0.002]		[0.002]		[0.008]
Medium-sized	0.366***	0.473***	0.535***	0.480***	0.448***	0.446***
	[0.027]	[0.040]	[0.025]	[0.030]	[0.076]	[0.099]
Large-sized	0.770***	1.078***	1.271***	1.123***	0.943***	0.948***
	[0.079]	[0.111]	[0.078]	[0.088]	[0.194]	[0.250]
Constant	0.252**	0.242*	-0.536***	-0.635***	-0.224	-0.229
	[0.099]	[0.137]	[0.125]	[0.133]	[0.248]	[0.373]
Observations	78448	37458	69361	35407	2266	1674
Firms	16431	6674	14413	6019	502	324
Wald test	157269.6	63173.9	68995.2	51296.2	8881.3	8315.6
Sargan	(0.000)	(0.000)	(0.000)	(0.000)	(0.018)	(0.005)
Hansen	(0.000)	(0.000)	(0.000)	(0.000)	(0.334)	(0.148)
AR(1)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.008)
AR(2)	(0.922)	(0.122)	(0.854)	(0.561)	(0.889)	(0.855)

Notes: All models include year and sector dummies (2-digit) but not reported to save space. All estimations were conducted with two-step efficient GMM. Robust standard errors clustered at sector level are reported in brackets *** p<0.01, ** p<0.05, * p<0.1. p-values for the tests (Sargan, Hansen, AR) are in parentheses.

Table A7: GMM-SYS Estimates with Size Class Dummies by Sub-Sectors: Model 1

	(10t12)	(13t15)	(16t18)	(19)	(20)	(21)	(22a23)	(24a25)	(26)	(27)	(28)	(29a30)	(31t33)
$Employment_{it-1}$	0.640***	0.515***	0.417*	1.245***	0.706***	0.081	0.166**	0.391***	0.745***	0.235*	0.308***	0.204	0.343**
	[0.074]	[0.073]	[0.219]	[0.194]	[0.130]	[0.301]	[0.084]	[0.091]	[0.135]	[0.123]	[0.096]	[0.129]	[0.137]
$Wage_{it}$	-0.145***	-0.142***	-0.102**	-0.238***	-0.149***	-0.225***	-0.201***	-0.132***	-0.204***	-0.116***	-0.161***	-0.176***	-0.211***
	[0.012]	[0.017]	[0.042]	[0.065]	[0.019]	[0.045]	[0.013]	[0.012]	[0.038]	[0.020]	[0.014]	[0.025]	[0.021]
$Output_{it}$	0.119***	0.183***	0.234***	0.104**	0.147***	0.290***	0.276***	0.229***	0.184***	0.291***	0.311***	0.309***	0.263***
	[0.014]	[0.015]	[0.058]	[0.044]	[0.042]	[0.108]	[0.021]	[0.025]	[0.043]	[0.038]	[0.032]	[0.041]	[0.027]
$NonICT_{it}$	0.003**	-0.002***	0.001	-0.008*	0.004	0.012	-0.000	0.001	-0.001	-0.001	0.003**	0.004*	-0.001
	[0.001]	[0.001]	[0.001]	[0.005]	[0.003]	[0.010]	[0.001]	[0.001]	[0.003]	[0.002]	[0.001]	[0.002]	[0.001]
ICT_{it}	0.001	-0.002	0.000	-0.004	0.002	0.011	0.005***	0.002	-0.004	0.006**	0.005***	0.007**	0.001
	[0.002]	[0.001]	[0.002]	[0.006]	[0.002]	[0.008]	[0.002]	[0.002]	[0.006]	[0.002]	[0.002]	[0.003]	[0.003]
Medium-sized	0.345***	0.430***	0.383***	-0.023	0.244***	0.720***	0.579***	0.452***	0.276***	0.470***	0.372***	0.531***	0.462***
	[0.042]	[0.045]	[0.109]	[0.159]	[0.072]	[0.169]	[0.044]	[0.043]	[0.077]	[0.059]	[0.039]	[0.063]	[0.067]
Large-sized	0.775***	0.909***	0.818***	-1.117**	0.450**	1.721***	1.374***	0.952***	0.439**	1.171***	0.956***	1.214***	1.041***
	[0.131]	[0.127]	[0.293]	[0.485]	[0.201]	[0.438]	[0.129]	[0.125]	[0.189]	[0.186]	[0.139]	[0.183]	[0.226]
Constant	0.618***	0.284*	-0.591*	-0.308	-0.019	0.496	0.515***	-0.174	0.087	-0.729***	-0.902***	-0.438	0.332
	[0.114]	[0.147]	[0.349]	[0.511]	[0.241]	[0.804]	[0.116]	[0.136]	[0.286]	[0.275]	[0.180]	[0.271]	[0.239]
Observations	16803	44442	7832	438	4235	827	20701	18076	1439	5283	11370	7093	11536
Firms	3383	9396	1691	120	911	154	4315	4085	348	1151	2600	1481	2909

Table A8: GMM-SYS Estimates with Size Class Dummies by Sub-Sectors: Model 2

	(10t12)	(13t15)	(16t18)	(19)	(20)	(21)	(22a23)	(24a25)	(26)	(27)	(28)	(29a30)	(31t33)
$Employment_{it-1}$	0.474***	0.018	0.640***	1.395***	0.839***	-0.005	0.229**	0.413***	0.785***	0.377***	0.370***	0.097	0.635***
	[0.100]	[0.132]	[0.135]	[0.270]	[0.143]	[0.386]	[0.099]	[0.142]	[0.255]	[0.142]	[0.098]	[0.196]	[0.084]
$Wage_{it}$	-0.156***	-0.139***	-0.079**	-0.336***	-0.142***	-0.243***	-0.171***	-0.126***	-0.234***	-0.099***	-0.155***	-0.235***	-0.137***
	[0.020]	[0.018]	[0.036]	[0.055]	[0.022]	[0.052]	[0.016]	[0.014]	[0.046]	[0.022]	[0.014]	[0.031]	[0.021]
$Output_{it}$	0.150***	0.278***	0.142***	0.040	0.097***	0.318**	0.259***	0.212***	0.194***	0.245***	0.273***	0.353***	0.155***
	[0.024]	[0.027]	[0.040]	[0.102]	[0.033]	[0.135]	[0.026]	[0.034]	[0.054]	[0.045]	[0.034]	[0.063]	[0.021]
$NonICT_{it}$	0.008***	0.004**	0.003	-0.008	0.001	0.007	0.000	0.003	-0.003	-0.000	0.002	0.010**	-0.002
	[0.002]	[0.002]	[0.002]	[0.014]	[0.004]	[0.013]	[0.002]	[0.002]	[0.005]	[0.002]	[0.002]	[0.004]	[0.001]
$ICTtang_{it}$	0.008	0.032***	0.006	-0.023	-0.008	0.042	0.005	0.004	-0.022	0.013	0.023***	0.037**	0.001
	[0.009]	[0.010]	[0.008]	[0.056]	[0.012]	[0.036]	[0.008]	[0.012]	[0.048]	[0.012]	[0.008]	[0.017]	[0.008]
$ICTintang_{it}$	0.009**	0.014***	-0.002	-0.008	0.002	0.019	0.010***	0.005	-0.006	0.007	0.006*	0.012	-0.004
	[0.004]	[0.004]	[0.003]	[0.028]	[0.005]	[0.024]	[0.004]	[0.003]	[0.012]	[0.005]	[0.004]	[0.009]	[0.003]
Medium-sized	0.437***	0.720***	0.293***	0.046	0.187*	0.802***	0.561***	0.426***	0.237*	0.399***	0.350***	0.555***	0.327***
	[0.058]	[0.079]	[0.072]	[0.170]	[0.100]	[0.239]	[0.055]	[0.064]	[0.134]	[0.064]	[0.039]	[0.096]	[0.045]
Large-sized	1.033***	1.701***	0.557***	-1.092**	0.331	1.836***	1.272***	0.931***	0.373	0.952***	0.857***	1.237***	0.647***
	[0.164]	[0.213]	[0.170]	[0.520]	[0.272]	[0.562]	[0.144]	[0.191]	[0.331]	[0.200]	[0.126]	[0.255]	[0.138]
Constant	0.591***	0.007	-0.307	1.374	0.445	0.119	0.233	-0.140	0.356	-0.813**	-0.850***	-0.744*	0.245
	[0.148]	[0.212]	[0.243]	[1.187]	[0.286]	[1.187]	[0.154]	[0.209]	[0.592]	[0.383]	[0.251]	[0.432]	[0.178]
Observations	6965	22238	4015	191	2499	659	9391	9205	1015	3142	6097	4128	4994
Firms	1100	4118	707	43	437	107	1575	1681	217	593	1175	720	1103

Table A9: Labor Demand Estimation Results with Alternative Variable: Full sample

	OLS	FE	GMM-D	GMM-S
Employment$_{it-1}$	0.781***	0.394***	0.001	0.554***
	[0.003]	[0.006]	[0.024]	[0.027]
Wage$_{it}$	-0.148***	-0.232***	-0.211***	-0.200***
	[0.004]	[0.011]	[0.011]	[0.007]
Output$_{it}$	0.182***	0.402***	0.379***	0.290***
	[0.002]	[0.005]	[0.006]	[0.011]
TotCAP$_{it}$	0.001***	0.005***	0.009***	0.004***
	[0.000]	[0.001]	[0.001]	[0.001]
ICTsh$_{it}$	-0.016	0.248***	0.258***	0.096***
	[0.012]	[0.057]	[0.052]	[0.025]
Constant	-0.641***	-1.893***		-1.137***
	[0.028]	[0.101]		[0.089]
Observations	150075	150075	117708	150075
Firms		30861	25278	30861
R-squared	0.883	0.517		
Wald test			12690.5	146350.4
Sargan			(0.060)	(0.000)
Hansen			(0.067)	(0.000)
AR(1)			(0.000)	(0.000)
AR(2)			(0.000)	(0.117)

Notes: All models include year and sector dummies (2-digit) but not reported to save space. Both GMM, difference (GMM-D) and system (GMM-S), were all conducted with two-step efficient GMM. Robust standard errors clustered at sector level are reported in brackets *** p<0.01, ** p<0.05, * p<0.1. p-values for the tests (Sargan, Hansen, AR) are in parentheses.

Table A10: Labor Demand Estimation with Alternative Variable by Technological Intensity (GMM-SYS estimates)

	Low-tech	Medium-tech	High-tech
Employment$_{it-1}$	0.744***	0.423***	0.592***
	[0.033]	[0.039]	[0.137]
Wage$_{it}$	-0.192***	-0.211***	-0.271***
	[0.014]	[0.008]	[0.039]
Output$_{it}$	0.204***	0.358***	0.304***
	[0.013]	[0.017]	[0.068]
TotCAP$_{it}$	0.001	0.005***	0.006
	[0.001]	[0.001]	[0.004]
ICTsh$_{it}$	0.007	0.152***	0.153
	[0.031]	[0.039]	[0.184]
Constant	-0.463***	-1.728***	-0.938*
	[0.133]	[0.181]	[0.480]
Observations	78448	69361	2266
Firms	16431	14413	502
Wald test	107548.4	57083.8	6536.6
Sargan	(0.000)	(0.000)	(0.028)
Hansen	(0.000)	(0.000)	(0.317)
AR(1)	(0.000)	(0.000)	(0.000)
AR(2)	(0.281)	(0.497)	(0.547)

Notes: All models include year and sector dummies (2-digit) but not reported to save space. All estimations were conducted with two-step efficient GMM. Robust standard errors clustered at sector level are reported in brackets *** p<0.01, ** p<0.05, * p<0.1. p-values for the tests (Sargan, Hansen, AR) are in parentheses.

Table A11: GMM-SYS Estimates with Alternative Variable by Sub-Sectors

	(10t12)	(13t15)	(16t18)	(19)	(20)	(21)	(22a23)	(24a25)	(26)	(27)	(28)	(29a30)	(31t33)
$Employment_{it-1}$	0.689***	0.760***	0.450***	1.081***	0.594**	0.288	0.459***	0.632***	0.838***	0.358***	0.424***	0.431***	0.560***
	[0.069]	[0.044]	[0.145]	[0.237]	[0.235]	[0.265]	[0.060]	[0.063]	[0.132]	[0.112]	[0.087]	[0.108]	[0.091]
$Wage_{it}$	-0.187***	-0.192***	-0.121***	-0.196**	-0.187***	-0.353***	-0.259***	-0.177***	-0.225***	-0.141***	-0.196***	-0.204***	-0.276***
	[0.015]	[0.020]	[0.043]	[0.098]	[0.026]	[0.071]	[0.016]	[0.014]	[0.047]	[0.023]	[0.016]	[0.032]	[0.027]
$Output_{it}$	0.172***	0.211***	0.337***	0.088	0.256**	0.472***	0.334***	0.254***	0.199***	0.395***	0.374***	0.364***	0.309***
	[0.023]	[0.019]	[0.063]	[0.074]	[0.109]	[0.156]	[0.025]	[0.027]	[0.060]	[0.054]	[0.041]	[0.051]	[0.032]
$TotCAP_{it}$	0.008***	-0.002**	0.002	-0.006	0.008	0.019**	0.004***	0.002	-0.003	0.006***	0.006***	0.007***	0.001
	[0.002]	[0.001]	[0.002]	[0.006]	[0.005]	[0.009]	[0.001]	[0.001]	[0.005]	[0.002]	[0.002]	[0.003]	[0.002]
$ICTsh_{it}$	-0.046	0.034	0.042	0.078	-0.086	-0.421	0.148*	0.045	-0.055	0.227*	0.107*	0.208*	0.057
	[0.074]	[0.047]	[0.096]	[0.598]	[0.149]	[0.668]	[0.077]	[0.059]	[0.223]	[0.131]	[0.061]	[0.121]	[0.079]
Constant	-0.059	-0.453**	-2.045***	0.095	-1.013	-1.691	-0.812***	-0.925***	-0.144	-2.565***	-1.955***	-1.822***	-0.466***
	[0.158]	[0.188]	[0.481]	[1.263]	[0.848]	[1.169]	[0.160]	[0.200]	[0.424]	[0.505]	[0.298]	[0.442]	[0.156]
Observations	16803	44442	7832	438	4235	827	20701	18076	1439	5283	11370	7093	11536
Firms	3383	9396	1691	120	911	154	4315	4085	348	1151	2600	1481	2909

Table A12: Labor Demand Estimation by Capital Intensity (GMM-SYS estimates)

	Lower capital intensity		Higher capital intensity	
$Employment_{it-1}$	0.473***	0.193	0.695***	0.647***
	[0.050]	[0.128]	[0.030]	[0.038]
$Wage_{it}$	-0.206***	-0.261***	-0.193***	-0.198***
	[0.014]	[0.024]	[0.009]	[0.011]
$Output_{it}$	0.289***	0.355***	0.233***	0.249***
	[0.016]	[0.037]	[0.014]	[0.016]
$NonICT_{it}$	0.006***	0.026***	0.005***	0.005***
	[0.001]	[0.004]	[0.001]	[0.001]
ICT_{it}	0.004**		0.006***	
	[0.002]		[0.001]	
$ICTtang_{it}$		0.016**		0.017***
		[0.007]		[0.005]
$ICTintang_{it}$		0.016***		0.008***
		[0.004]		[0.002]
Constant	-0.792***	-0.783***	-0.920***	-1.096***
	[0.125]	[0.241]	[0.112]	[0.150]
Observations	62943	8239	87132	66300
Firms	17003	2285	16868	11655
Wald test	22613.2	2638.1	197178.1	153343.4
Sargan	(0.000)	(0.000)	(0.000)	(0.000)
Hansen	(0.000)	(0.000)	(0.000)	(0.000)
AR(1)	(0.000)	(0.019)	(0.000)	(0.000)
AR(2)	(0.106)	(0.754)	(0.482)	(0.750)

Notes: All models include year and sector dummies (2-digit) but not reported to save space. All estimations were conducted with two-step efficient GMM. Robust standard errors clustered at sector level are reported in brackets *** p<0.01, ** p<0.05, * p<0.1. p-values for the tests (Sargan, Hansen, AR) are in parentheses.

Table A13: GMM-SYS Estimates by 2-Digit Sectors: Model 1

	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
$Employment_{it-1}$	0.606***	0.636***	0.347	0.143	0.898***	0.872***	0.364	0.770***	0.243	0.843**	0.574***	0.277
	[0.072]	[0.177]	[0.519]	[0.099]	[0.042]	[0.099]	[0.291]	[0.089]	[0.511]	[0.351]	[0.150]	[0.381]
$Wage_{it}$	-0.193***	-0.275***	-0.692*	-0.216***	-0.214***	-0.246***	-0.187*	-0.081***	-0.048	-0.131	-0.192***	-0.347***
	[0.015]	[0.069]	[0.381]	[0.021]	[0.032]	[0.031]	[0.108]	[0.028]	[0.057]	[0.120]	[0.023]	[0.097]
$Output_{it}$	0.199***	0.263***	0.478	0.487***	0.189***	0.188***	0.384***	0.194***	0.417**	0.169	0.265***	0.481**
	[0.022]	[0.085]	[0.372]	[0.044]	[0.017]	[0.032]	[0.106]	[0.042]	[0.191]	[0.107]	[0.070]	[0.221]
$NonICT_{it}$	0.011***	0.006	0.019	0.005**	-0.007***	-0.001	0.005	-0.002	0.005	-0.007*	0.009**	0.022
	[0.002]	[0.004]	[0.022]	[0.002]	[0.001]	[0.002]	[0.003]	[0.001]	[0.007]	[0.004]	[0.004]	[0.018]
ICT_{it}	0.011***	0.003	-0.013	0.021***	-0.008***	-0.004	-0.001	0.001	0.001	0.004	0.007**	0.015
	[0.003]	[0.007]	[0.033]	[0.004]	[0.001]	[0.004]	[0.007]	[0.003]	[0.006]	[0.015]	[0.003]	[0.012]
Constant	-0.198	-0.284	1.608	-2.425***	-0.248	-0.030	-1.764	-1.369***	-3.220**	-0.907	-1.095*	-2.065
	[0.149]	[0.829]	[1.063]	[0.365]	[0.259]	[0.295]	[1.223]	[0.349]	[1.573]	[1.501]	[0.563]	[1.724]
Observations	15828	825	150	17454	23416	3572	2325	3262	2245	438	4235	827
Firms	3163	201	26	3459	5366	785	557	681	529	120	911	154

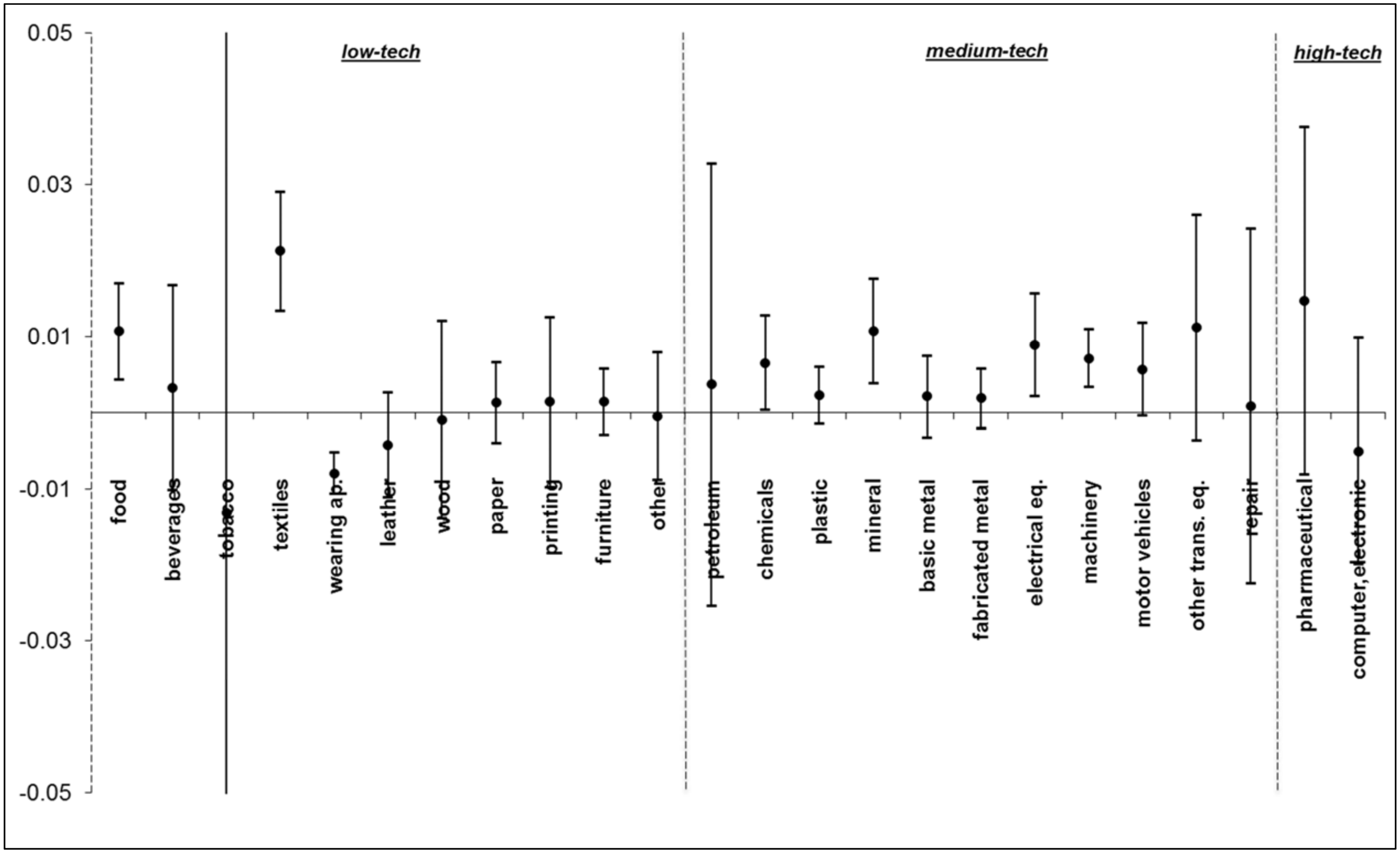
	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)	(31)	(32)	(33)
$Employment_{it-1}$	0.556***	0.416***	0.681***	0.597***	0.851***	0.394***	0.432***	0.575***	0.375**	0.462***	0.951***	0.162
	[0.072]	[0.081]	[0.098]	[0.065]	[0.132]	[0.120]	[0.076]	[0.118]	[0.172]	[0.083]	[0.122]	[0.384]
$Wage_{it}$	-0.134***	-0.330***	-0.094***	-0.226***	-0.227***	-0.144***	-0.207***	-0.201***	-0.165***	-0.236***	-0.179***	-0.376***
	[0.019]	[0.023]	[0.016]	[0.018]	[0.044]	[0.024]	[0.015]	[0.024]	[0.043]	[0.022]	[0.043]	[0.080]
$Output_{it}$	0.294***	0.352***	0.198***	0.314***	0.202***	0.380***	0.374***	0.315***	0.313***	0.389***	0.105***	0.514***
	[0.032]	[0.031]	[0.041]	[0.027]	[0.058]	[0.057]	[0.034]	[0.058]	[0.064]	[0.038]	[0.034]	[0.099]
$NonICT_{it}$	0.000	0.002	0.006**	-0.001	-0.003	0.001	0.004***	0.003	0.004	0.002	-0.002	-0.014**
	[0.001]	[0.002]	[0.002]	[0.001]	[0.003]	[0.002]	[0.001]	[0.002]	[0.005]	[0.002]	[0.003]	[0.006]
ICT_{it}	0.002	0.011***	0.002	0.002	-0.005	0.009***	0.007***	0.006*	0.011	0.001	-0.000	0.001
	[0.002]	[0.004]	[0.003]	[0.002]	[0.008]	[0.003]	[0.002]	[0.003]	[0.008]	[0.002]	[0.004]	[0.012]
Constant	-1.568***	-0.251	-1.134***	-1.127***	-0.190	-2.315***	-1.817***	-1.434***	-1.205***	-1.578***	0.299	-0.646
	[0.296]	[0.168]	[0.386]	[0.183]	[0.389]	[0.498]	[0.242]	[0.548]	[0.464]	[0.321]	[0.410]	[0.738]
Observations	9313	11388	5220	12856	1439	5283	11370	5561	1532	6181	3190	2165
Firms	2004	2339	1100	3141	348	1151	2600	1075	412	1385	725	815

Table A14: GMM-SYS Estimates by 2-Digit Sectors: Model 2

	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
Employment$_{it-1}$	0.481***	0.609***	0.603	-0.249	0.800***	0.886***	0.547***	0.767***	0.793***	1.996**	0.440	0.286
	[0.114]	[0.152]	[0.533]	[0.242]	[0.063]	[0.111]	[0.168]	[0.098]	[0.211]	[0.793]	[0.357]	[0.368]
Wage$_{it}$	-0.258***	-0.277***	-0.619*	-0.228***	-0.299***	-0.248***	-0.247***	-0.063**	-0.109**	-0.489**	-0.203***	-0.366***
	[0.031]	[0.094]	[0.375]	[0.038]	[0.027]	[0.041]	[0.046]	[0.027]	[0.045]	[0.242]	[0.042]	[0.099]
Output$_{it}$	0.272***	0.303***	0.188	0.652***	0.224***	0.184***	0.318***	0.163***	0.196**	-0.168	0.315**	0.489**
	[0.043]	[0.086]	[0.272]	[0.101]	[0.026]	[0.046]	[0.062]	[0.046]	[0.094]	[0.204]	[0.155]	[0.216]
NonICT$_{it}$	0.019***	0.011	0.017	0.012**	-0.003*	-0.003	0.002	0.001	0.002	-0.034	0.013	0.015
	[0.004]	[0.008]	[0.026]	[0.005]	[0.002]	[0.003]	[0.003]	[0.002]	[0.004]	[0.042]	[0.010]	[0.021]
ICTtang$_{it}$	0.032**	-0.034	0.119	0.131***	-0.013	-0.013	0.015	0.017	0.001	-0.190	0.019	0.047
	[0.015]	[0.027]	[0.125]	[0.036]	[0.010]	[0.010]	[0.026]	[0.010]	[0.014]	[0.206]	[0.023]	[0.051]
ICTintang$_{it}$	0.020***	0.005	0.012	0.039***	-0.009***	-0.005	-0.003	0.000	-0.003	0.013	0.019	0.017
	[0.007]	[0.012]	[0.085]	[0.012]	[0.003]	[0.011]	[0.006]	[0.005]	[0.006]	[0.053]	[0.014]	[0.030]
Constant	-0.794**	-0.365	2.547***	-5.036***	0.448	0.149	-1.044**	-1.287***	-1.242	6.361	-1.606	-2.391
	[0.320]	[0.797]	[0.915]	[1.141]	[0.295]	[0.396]	[0.438]	[0.424]	[0.912]	[4.780]	[1.359]	[2.070]
Observations	6394	442	129	8899	11786	1553	847	1855	1313	191	2499	659
Firms	1007	76	19	1500	2441	280	162	335	257	43	437	107

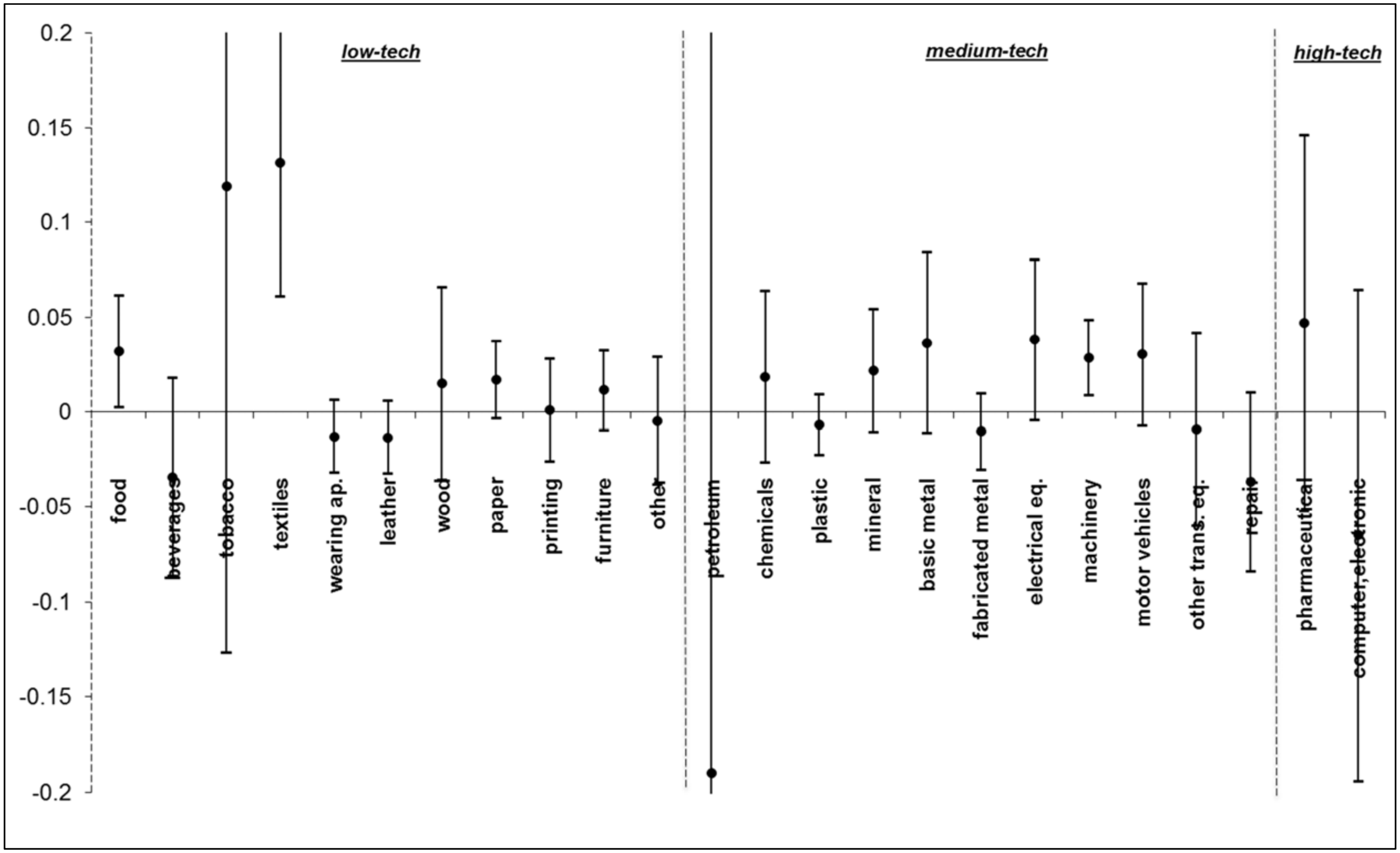
	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)	(31)	(32)	(33)
Employment$_{it-1}$	0.559***	0.386***	0.598***	0.659***	1.053***	0.429**	0.460***	0.536***	0.585***	0.504***	1.066***	0.578**
	[0.100]	[0.131]	[0.162]	[0.082]	[0.278]	[0.171]	[0.093]	[0.168]	[0.209]	[0.110]	[0.132]	[0.242]
Wage$_{it}$	-0.165***	-0.322***	-0.069***	-0.235***	-0.245***	-0.120***	-0.210***	-0.217***	-0.240***	-0.231***	-0.106*	-0.163***
	[0.022]	[0.038]	[0.022]	[0.021]	[0.059]	[0.027]	[0.019]	[0.027]	[0.057]	[0.033]	[0.062]	[0.060]
Output$_{it}$	0.307***	0.378***	0.204***	0.310***	0.162*	0.350***	0.355***	0.323***	0.285***	0.379***	0.061	0.297***
	[0.045]	[0.055]	[0.061]	[0.038]	[0.089]	[0.078]	[0.043]	[0.080]	[0.084]	[0.059]	[0.043]	[0.078]
NonICT$_{it}$	0.000	0.003	0.010***	-0.000	-0.005	0.002	0.004**	0.006	0.007	0.001	-0.008**	-0.003
	[0.002]	[0.003]	[0.004]	[0.002]	[0.005]	[0.003]	[0.002]	[0.004]	[0.008]	[0.002]	[0.004]	[0.006]
ICTtang$_{it}$	-0.007	0.022	0.036	-0.010	-0.065	0.038*	0.029***	0.030	-0.009	0.012	-0.005	-0.037
	[0.008]	[0.017]	[0.024]	[0.010]	[0.066]	[0.022]	[0.010]	[0.019]	[0.026]	[0.011]	[0.017]	[0.024]
ICTintang$_{it}$	0.011**	0.020**	0.003	0.003	-0.017	0.011*	0.011**	0.004	0.014	-0.008**	-0.008	0.002
	[0.005]	[0.009]	[0.006]	[0.003]	[0.018]	[0.006]	[0.005]	[0.008]	[0.015]	[0.004]	[0.007]	[0.011]
Constant	-1.452***	-0.853***	-1.695**	-1.101***	0.739	-2.647***	-1.938***	-1.608**	-0.695	-1.646***	0.106	-0.829**
	[0.424]	[0.313]	[0.772]	[0.278]	[1.027]	[0.854]	[0.367]	[0.806]	[0.586]	[0.547]	[0.671]	[0.388]
Observations	4980	4411	2815	6390	1015	3142	6097	3361	767	2719	1521	754
Firms	857	726	491	1264	217	593	1175	549	175	516	296	298

Figure A1: Coefficient Estimates of ICT Capital with 95 % Confidence Intervals by 2-Digit Sectors



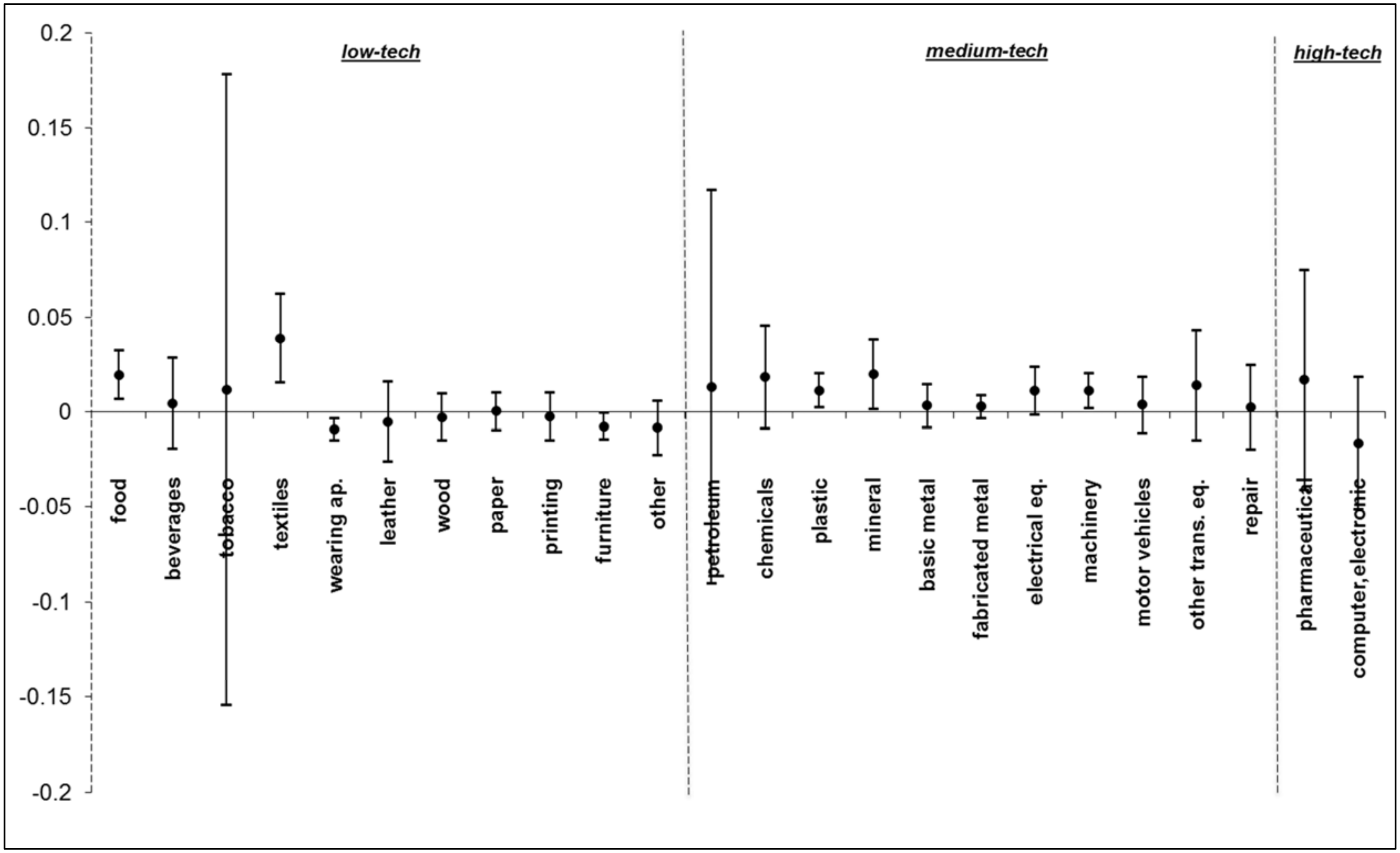
Note: See Table A13 for full estimation results of model 1 by 2-digit sectors.

Figure A2: Coefficient Estimates of Tangible ICT Capital with 95 % Confidence Intervals by 2-Digit Sectors



Note: See Table A14 for full estimation results of model 2 by 2-digit sectors.

Figure A3: Coefficient Estimates of Intangible ICT Capital with 95 % Confidence Intervals by 2-Digit Sectors



Note: See Table A14 for full estimation results of model 2 by 2-digit sectors.