International Journal of New Political Economy 3(2): 27-50, 2022

IJEP **International Journal of New Political Economy**

DOI: 10. 52547/jep.3.2.27

Total Factor Productivity and Intangible Capital in Different Levels of Technology: A Case Study of Iranian Manufacturing Industries

Forough EsmaeilySadrabadi[1], Esfandiar Jahangard[2]

ARTICLE INFO

Article history:
Date of submission: 08-02-2022
Date of acceptance: 09-05-2022

JEL Classification:
O31, O32
O32, O40

Keywords:
ARDL Model
Intangible Capital
TFP, ICT
Level of Technology

ABSTRACT

This article tries to examine intangible investment in different levels of Iranian industrial technology by using a comprehensive measure of intangible capital costs in Iran from 1996 to 2018. Previous studies in the study of intangible capital on total factor productivity (TFP), show that intangible investment has a positive and significant effect on this variable in Iran's manufacturing industry with a four-digit ISIC code. Also among the components, Information and Communication Technology (ICT) has a more prominent role on the TFP variable. This study examines all the factors (which play a role in measuring intangible investment) on the growth of TFP at different levels of technology (which are divided into four categories).Unlike previous studies, for all industries, apart from technology levels, ICT is very effective and other components are ignored, the results of this study show that other factors affect intangible investment except ICT in high-tech and medium / high industries have higher impact on TFP than ICT and vice versa. It is also suggested to achieve the highest optimal level of TFP, by separating different levels of technology, to focus on components such as research and development, brand, educational services, etc. for high levels and ICT factor for low levels.

1. Introduction

Capital is what builds up the capital which together with labor, constitutes the two measured inputs to production that power the economy, the sinews and joints by which cause the economy to work. Traditionally, when economists measured capital, they were measuring capital in physical goods,

This article is extracted from the doctoral thesis of the Forough EsmaeilySadrabadi

1. Ph.D Candidate of Economics, Faculty of Economics, Allameh Tabataba'i University, Tehran, Iran (Corresponding Author), E-mail address: fesmaeily@gmail.com
2. Associate Professor, Faculty of Economics, Allameh Tabatabai University, Tehran, Iran.

plants, and machinery. However, with the advent of the internet in the 1990s, based on what economists began to recognize as the results of research and development (R&D) and the largely nonphysical ideas resulting from it the idea of a new "knowledge economy" emerged. If this new economy were measured by economists, the valuation of these intangible assets would need to be incorporated into their models of economic growth (Haskel et al., 2017). In order to measure intangible capital in Iran, we follow the approach of Corrado et al., (2005; 2006), (abbreviated as CHS hereafter), those who classify intangibles into three major types of assets: computerized information, innovative property, and economic competencies. Computerized information consists of, for instance, software and databases. The innovative property includes scientific and nonscientific R&D, where the latter refers to, for example, mineral exploitation, copyright and license costs, and other product development, design, and research expenses. Economic competencies, finally, include brand equity, firm-specific human capital, and organizational structure. The average ratio of intangible capital to production in Iranian industries with four-digit ISIC code is 68.41%[1], which is a considerable Fig. Therefore, this type of capital is effective for TFP growth. Dividing Iran's manufacturing industries into different levels of technology is the purpose of this research. In this study, industries are divided into four parts, from high-tech industries to low-level industries. For all levels, the effect of all intangible investment components (into two parts, all components except ICT and ICT) on TFP growth is investigated for answering this question, do all components of intangible investment have the same effect on different levels of technology in Iran's manufacturing industries? It should be noted that the studied data for measuring intangible investment are four-digit ISIC codes for Iranian industries for employees of ten or more during the years 1996 to 2018 and the model used is the panel by GMM method.

1. Authors' own calculation

This paper consists of five sections. In the section 2, we review previous studies in the field of measuring intangible capital. In the section 3, analysis the relationship between intangible capital and TFP, and the classification of industries. Next, we estimate intangible capital following the methodology developed by Corrado et al. (2005; 2006) and examined its effect on TFP growth. In section 4, industries are classified based on technology intensity and the effectiveness of intangible capital on TFP growth tested. The last section summarizes the results and their policy implications and discusses future tasks.

2. Literature Review

There have been many studies on how to measure intangible capital. The first study was conducted in 2005 by Corrado, Hulten, and Sichel. As illustrated in table 1, they group the various items into three broad categories: computerized information, innovative property, and economic competencies.

Table 1. Business intangibles, by broad group

Name of group	Type of knowledge capital	Current status in the NIPAs
Computerized information	Knowledge embedded in computer programs and computerized databases	Major component,computer software,is capitalized
Innovative property	Knowledge acquired through scientific R&D and nonscientific inventive and creative activities	Most spending for new product discovery and development is expensed
Economic competencies	Knowledge embedded in firm-specific human and structural resources,including brand names	No items recognized as assets of the firm

[a]. Two small components-oil and gas exploration, and architectural and engineering services embedded in structures and equipment purchases—are included in the NIPA business fixed capital.

Source: Corrado et al. (2005)

Computerized information includes computer 1.software and 2.computer database. The innovative property contains 3.science and engineering research and development, 4.science and engineering research and development, 5.copyright and licenses for the development of entertainment and art, and 6.other costs of product development, design, and research. Economic competencies include 7.equity, 8.company-specific human capital, and 9.Organizational structure. They continued their studies to achieve a comprehensive segmentation of intangible capital until 2014 (Corrado et al., 2009; Corrado et al., 2012; Corrado et al., 2014). Recently, they answered the question can artificial intelligence (AI) raise productivity? In a study entitled “Artificial Intelligence and Productivity: An Intangible Asset Approach". The approach used in this study is the same as the CHS approach (Corrado et al., 2021). Liang (2021) used a quantitative growth model with intangible capitals and endogenously variable markups, along with U.S. manufacturing. In his article, he points out that he has used the CHS approach to calculate intangible capital. There have been many studies on the impact of intangible capital on productivity in the world. Van Ark and Timmer (2008) showed the cause of reduction of labor productivity growth in Europe compared to labor productivity growth in the United States, is the slower emergence of the knowledge economy in Europe. Bhattacharya and Rath (2020) examined the impact of innovation on labor productivity by using the latest World Bank Enterprise Surveys data and compares the results between the Chinese and Indian manufacturing sectors. They found that innovation affects the labor productivity positively for Chinese as well as Indian manufacturing firms, but its impact on firm productivity is relatively weak in the case of India as compared to China. Rico and Cebrer-Bares (2020) found a positive effect of intangible capital on Spanish companies’ productivity. Hintzmann et al. (2021) examined the labor productivity growth in the manufacturing sector in a different set of 18 European countries between 1995 and 2017. The main findings are all the three different categories (CHS approach) of intangible assets contribute to labor productivity growth. In particular, intangible assets related to economic competencies have been identified as the main drivers.

The impact of ICT factors on the development of economic and economically driven processes is indisputable. ICT is an important component in measuring intangible capital, so there are many studies on its effect on economic variables. Lefophane and Kalaba (2021) estimated the effects of ICT intensity on labor productivity, employment, and output of agro-processing industries. The findings suggest that ICT intensity yields higher positive and significant effects on the growth of the more ICT-intensive industries. Kim et al. (2021) studied the contribution of information and communication technology (ICT) to productivity both directly – and indirectly. Sawng et al. (2021) investigated how capital in the industry of ICT has been interlocked with the GDP growth of South Korea. The results revealed that ICT and GDP growth affected positively.

Lall (2000) characterized industries with different levels of technologies. Soltanisehat et al. (2019) examined the role of R&D expenditures in TFP growth in Iran’s industry sector. They revealed that R&D expenditures in high-tech and medium/high-tech industries have a positive effect on TFP growth. Bhattacharya et al. (2021) explored whether the moderating effect of R&D intensity differs for firms in high-tech versus low-tech sectors. They investigated that, unlike low-tech firms, high-tech firms with higher R&D intensity in the previous period derive substantial productivity gains from FDI and the utilization of imported inputs and capital goods.

3. Intangible Capital

We follow the CHS approach, for measuring the intangible capital. Influential components for estimating intangible capital in Iranian industries include: Computer software, information and communication, research and development, laboratory research, advertising, exhibition, press, and educational services. To measure intangible capital, we used the data of Iranian factory by four-digit ISIC code during the years 1996 to 2018. In total, 135 four-digit ISIC codes have been used in the calculations, and the total number of data for the years 1996 to 2018 is 2190 (EsmaeilySadrabadi et al,2021). The data shows the ratio of 68.41% for the intangible capital of production for all industries, which reveals a high impact of intangible capital on Iranian industries[1].

3.1. Intangible Capital and TFP: A Theoretical Analysis

The function of traditional Cobb–Douglas production includes the conventional inputs of physical capital and labor is formulated as:

$$Y_{it} = A_i K_{it}^{\beta_1} L_{it}^{\beta_2} e^{it} \tag{1}$$

Where Y is value added; K is the stock of capital; L is labor units; A stands for the efficiency level; u is an error term; i = 1, 2, …, N = 135 four-digit ISIC codes, and t = 1, 2,…, T = 23 (for the period of 1996–2018).The production function is estimated in a log-linear form within a lag framework. The model of empirical panel is specified as follows:

$$LTFP_{it} = \alpha_i + \beta_1 \Delta lnL_{i,t} + \beta_2 \Delta lnK_{i,t} + \beta_3 \Delta lnR_{i,t} + \beta_4 LTFP_{i,t-1} + u_{it} \tag{2}$$

R is a real intangible capital. The main method of calculating inventory capital (tangible-intangible) which we used is the Perpetual Inventory Method (PIM) (Meinen et al., 1998). The Divisia index was also used to estimate TFP (Diewert, 1993; Divisia, 1925; 1926).

3.2. Intangible Capital and ICT: A Theoretical Analysis

The main model of interest builds upon the following general production function:

$$V_{i,t} = A_{i,t} . F\left(L_{i,t}, K_{i,t}\right) \tag{3}$$

1. The Statistics Center of Iran has been used to obtain the data. The years used are from 1375 to 1396. The estimated components are intangible investment, physical investment, labor force and production volume, to calculate the productivity index of production factors. The obtained data have been used separately according to the economic activity ranking classification code with version 4 from the Statistics Center of Iran. In the codes, we merged them with similar codes, and as a result, the number of codes is 132, which is the total number of data for the years 1996 to 2018 is equal to 2190, and the volume of data is worth considering for the correct estimation.

Where V denotes value added adjusted to include intangible capital[1]. A is the Hicks-neutral technology parameter that allows for changes in productivity with which labor (L) and capital (K) are transformed into output. The subscripts c, i, t indicate country, industry, and year. Suppose total capital input K is composed of three types: non-ICT (NICT), ICT, and intangible capital (INT) and assume a Cobb-Douglas functional form for the production function. Equation (3) can be written out as follows:

$$V_{i,t} = A_{i,t}.L^{\alpha}{}_{i,t}\left(K^{NICT}{}_{i,t}\right)^{\beta 1}\left(K^{ICT}{}_{i,t}\right)^{\beta 2}\left(K^{INT}{}_{i,t}\right)^{\beta 3} \tag{4}$$

Where L denotes labor input measured by labor services, which accounts for differences in labor qualities (i.e. human capital) ; K is the capital services provided by non-ICT, ICT, and intangible capital. The output elasticity is labeled as the superscripts α and βX, x = (1, 2, 3). After taking logs and first differences and assuming constant returns to scale, equation (4) can be rewritten as:

$$\Delta\left(v-l\right)=\beta_1\Delta(K^{NICT}-l)+\beta_2\Delta\left(K^{ICT}-l\right)+\beta_3\Delta\left(K^{INT}-l\right)+\mu \tag{5}$$

where lower-case denote variables in natural logarithms and the subscripts are suppressed for simplicity of exposition. The efficiency term A is modeled as part of the error term μ. For reasons explained below, the error term is decomposed into a country-industry specific fixed effect wc, i, t, a full set of time dummies τt, and an idiosyncratic component εc, i, t. To examine whether the output elasticity of intangible capital differs across industries with varying degrees of ICT intensity, intangible capital has interacted with an ICT intensity indicator (DICT c, i) that is measured as the ratio of ICT capital services to labor services: [2]

---

1. Value added is used as the output measure because: (1) there is no readily available intangibles data on gross output; and (2) labour productivity based on value added is measured more accurately in the presence of outsourcing, a feature that is commonly observed at the industry level (Schreyer & Pilat,2001)
2. This is one of the most commonly used measures for (ICT) capital intensity (e.g. Corrado et al., 2014). Other proposed measures, such as ICT capital compensation as a share of total value added (e.g. Jorgenson al Timmer, 2011; Michaels et al., 2014) and ICT capital share of total capital services (e.g. Stiroh, 2002), are considered in sensitivity analysis.

$$\Delta(v-l)=\beta_1\Delta\left(k^{NICT}-l\right)+\beta_2\Delta\left(k^{ICT}-l\right)+\beta_3\Delta\left(k^{INT}-l\right)$$
$$+\gamma\Delta\left(k^{INT}-l\right).D^{ICT}{}_i+w^{ICT}{}_i+\tau_t+\epsilon_{i,t} \tag{6}$$

This specification is similar to the difference-in-difference approach which has its antecedents in the literature that analyses the impact of financial development on industry growth (Rajan & Zingales, 1998) and has been used in the previous work on productivity in ICT-intensive industries (Corrado et al., 2014). If the complementarity hypothesis holds true, it is expected to be positive and statistically significant. Given that ICT capital is highly correlated with intangible capital (the correlation coefficient is larger than 0.8), one may argue that it is perhaps not intangible capital that has a higher output elasticity in ICT-intensive industries but ICT capital itself or even non-ICT assets. To account for these potential omitted variable biases, the full model is specified as follows:

$$\Delta(v-l)=\gamma_1\Delta\left(k^{NICT}-l\right).D^{ICT}{}_i+\gamma_2\Delta\left(k^{ICT}-l\right).D^{ICT}{}_i$$
$$+\gamma_3\Delta\left(k^{INT}-l\right).D^{ICT}{}_i+\beta X'+w_i+\tau_t+\epsilon_{i,t} \tag{7}$$

where X' indicates the vector of the main variables including the growth of capital inputs. γ_1 and γ_2 are not expected to be different from zero, as there is no theoretical underpinning for assets other than intangibles to complement ICT capital. To ensure a meaningful interpretation for the coefficients of the variables of interest, the interaction terms are demeaned for estimation following the suggestion of Balli and Sørensen[1] (2013).

3.3. Econometric Results

Fig 1 shows the trend of intangible capital and output changes over a 23-year period. The ascending chart shows the positive relationship between these

1. From an econometric point of view, demeaning the interaction term does not change the result. It is a parameterization of the same statistical model, but the added benefit is that the coefficient estimates of the main variables will remain similar to the simple model without the interaction term. As for the coefficient estimate of the interaction term as well as its standard errors, it will be exactly identical whether the interaction variables are demeaned or not.

two variables. Fig 2 shows the share between ICT and non-ICT in the total intangible capital. Among the studied codes, production of motor vehicles, manufacturing of measuring equipment, production of iron and steel, etc. have the highest share of ICT in intangible capital. Production of air and space vehicles, production and repair of ships, production of office machinery and accounting, etc. have the highest share of factors other than ICT (such as research and development, innovation, brand, etc.) and it is noteworthy that these codes are in a subset of high-tech industries which will be explained in the next section (EsmaeilySadrabadi et al., 2021). Fig 3 represents skilled and unskilled labor by four-digit ISIC code. Production of electric motors, dynamos and transformers and power distribution and control devices, production of raw iron and steel products, production of other chemical products, preparation and spinning of textile fibers - textiles, etc. have the highest level of skilled labors. Cleaning, grading, and packing dates, processing and protecting fish and other marine animals from spoilage, dairy production, sugar production, etc. have the highest unskilled labor force (EsmaeilySadrabadi et al., 2021).

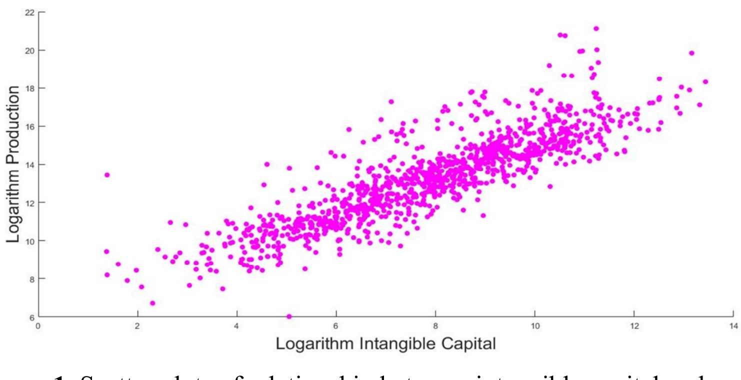

Figure 1. Scatter plots of relationship between intangible capital and output

Source: Authors' own calculation

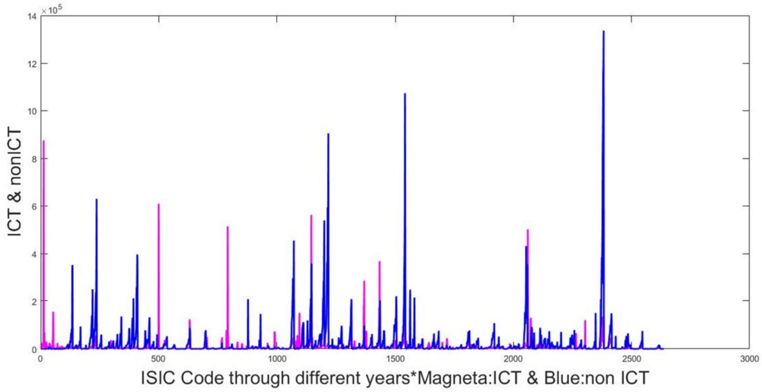

Figure 2. Share of ICT and non-ICT in the total intangible capital

Source: EsmaeilySadrabadi et al (2021)

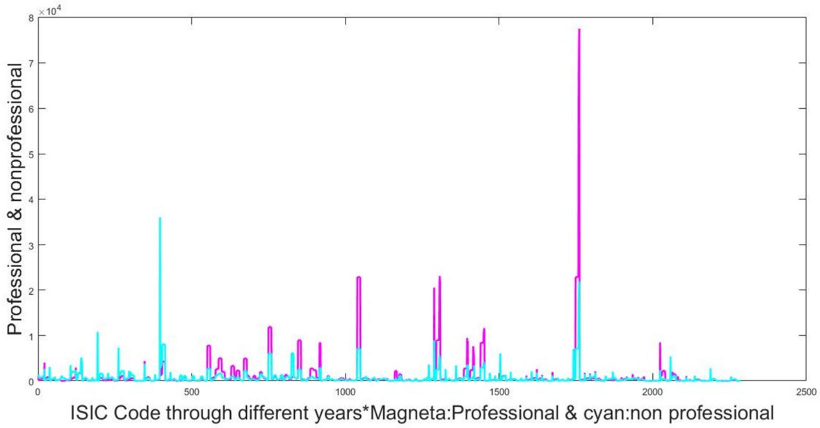

Figure 3. Ratio of skilled and unskilled labor to the total labor force

Source: EsmaeilySadrabadi et al. (2021)

The emergence of GMM models in industrial research when using panel data can resolve some of the unanswered questions raised in the recent literature when discussing econometric techniques. Arellano and Bond (1991) and Blundell and Bond (1998) developed the generalized method of the moments model, which can be used for dynamic panel data. In dynamic panel data, the cause and effect relationship for underlying phenomena is generally dynamic over time. For example, it may not be the current year's TFP that is affecting performance, but the previous year's TFP that could be playing a significant role. To capture this, dynamic panel data estimation techniques use lags of the dependent variables as explanatory variables. Lagged values of the dependent variables are therefore used as instruments to control this endogenous relationship. These instruments are often called 'internal instruments' as they are used from the existing econometric model (Roodman, 2009). The GMM model, which is generally used for panel data, provides consistent results in the presence of different sources of endogeneity, namely "unobserved heterogeneity, simultaneity and dynamic endogeneity" (Wintoki et al., 2012: 588). Traditionally, researchers (Schultz et al., 2010; Wintoki et al., 2012) have used two lags of the dependent variables and they argue that two lags are sufficient to capture the persistence of the dependent variable (say for example firm performance).

Roodman (2009) presented some assumptions that need to be fulfilled when employing GMM estimations, namely (a) some regressors may be determined endogenously; (b) the nature of the relationship is dynamic, implying that current performance is affected by previous ones; (c) the idiosyncratic disturbances are uncorrelated across individual; (d) some regressors may not necessarily be strict exogenous; and finally, (e) the time periods in panel data, T, might be small. (i.e., "small T, large N."). The inclusion of lag performance variables changes the static nature of this econometric model to a dynamic panel data model. Two-step system GMM relies on internal instruments (lagged values, internal transformation) to address the different sources of endogeneity discussed in the literature review section.

The explanatory variables used in this research are "TFP", "Intangible Capital(INT)", "ICT", "Intangible Capital, except ICT(NICT)", "Labor(L)", "Professional Labor (PROFL)", " Non-Professional Labor(NONPROF)" and

"Physical Capital(K)"[1]. Table 2 shows descriptive statistics for all industries without industry classification based on technology level by adding the results of previous studies (EsmaeilySadrabadi et al., 2021).

Table 2. Intangible Capital and TFP growth: panel OLS and first difference GMM estimation [a]. Dependent Variable: INT, K, L, ICT, NICT, PROFL, NONPROF

Regressors	1		2		3	
	GMM	**FE**	**GMM**	**FE**	**GMM**	**FE**
LTFP(-1)[b]	0.440 (0.000)	-	0.391 (0.000)	-	0.370 (10.000)	-
LINT	0.356 (0.001)	0.482 (0.017)	0.398 (0.001)	0.553 (0.016)	-	-
LL	0.228 (0.003)	0.363 (0.035)	-	-	0.032 (0.002)	0.194 (0.034)
LK	0.234 (0.001)	0.372 (0.014)	0.281 (0.000)	0.405 (0.014)	0.269 (0.000)	0.194 (0.034)
NICT	-	-	-	-	0.029 (0.001)	0.030 (0.016)
ICT	-	-	-	-	0.509 (0.001)	0.645 (0.019)
PROFL	-	-	0.064 (0.002)	0.091 (0.018)	-	-
NONPROF	-	-	0.009 (0.003)	0.074 (0.021)	-	-
$\bar{R}^2$	0.924	-	0.92	-	0.918	-
N[c]	2283	1874	2177	1944	2219	2008
Sargan J-statistic	129.96 (43.47)	-	126.95 (0.509)	-	130.97 (0.386)	-
Instrument Rank	132	-	133	-	132	-
S.E. of regression	0.568	-	0.477	-	0.594	-
Arellano-Bond Serial Correlation Test	AR(1):-3/57 (0.000) AR(2):1.59 (0.109)	-	AR(1):-4.003 (0/0001) AR(2):0.819 (0.412)	-	AR(1):-4.559 (0.000) AR(2):1.361 (0.173)	-

[a.] One-step GMM estimator with robust standard error. [b]l : logarithm, [c] Number of observations

Source: Authors' own calculations and EsmaeilySadrabadi et al. (2021)

1. All variables used in the model are static.

As can be seen, contrary to the traditional approach, intangible capital is not included in intermediate goods, but as an important factor in the production function. The employment impact factor, including professional and non-professional labor, is approximately equal to 0.22, which has a positive and significant effect on TFP. Also, this coefficient for physical capital and intangible capital is approximately 0.23 and 0.35 (respectively) in the same direction on average. A noteworthy point is the impact of intangible capital, which indicates that in order to increase TFP, instead of focusing on physical capital such as building construction, it should focus on ICT, research and development, and so on. By estimating the second model, which divides the labor force into skilled and unskilled labor force, the skilled labor force coefficient is approximately seven times that of the unskilled labor force, which indicates that the skilled labor force (skilled, professional, and literate) has a greater effect on TFP[1].

The results of the third regressor show that the impact of ICT capital on the productivity of production factors is on average 50%, which is a significant Fig. In general, the ICT variable has a positive and significant effect on TFP. But the rest of the intangible capital components do not weigh much. In fact, these results show that the main component of intangible capital that has a great impact on TFP is ICT, and components such as research and development, educational services, brand, advertising, etc. have little effect[2].

That is why in the next section we have divided the industries with the type of technology to answer the question of whether the same results are achieved through all levels of technology.

4. Different Levels of Technology

According to Lall (2000), characteristics of industries with different levels of technologies are summarized as follow:

1. For further information, you can refer to the EsmaeilySadrabadi et al., 2021 study
2. For further information, you can refer to the EsmaeilySadrabadi et al., 2021 study

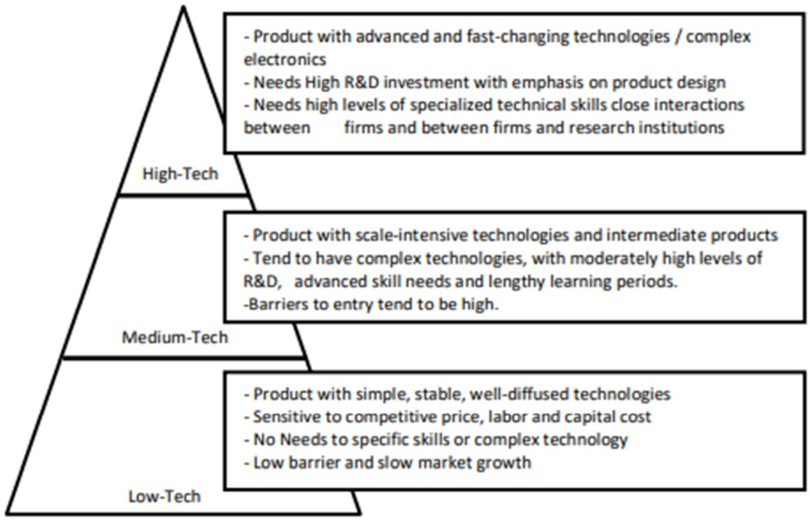

Figure 4. Characteristic of Industries with Different Technological Level

Source: Lall (2000)

According to the classification performed by the Organization for Economic Cooperation and Development in 2011 (OECD, 2011), all industries are divided into four groups of high-tech industries, medium/high-tech industries, medium/low-tech industries, and low-tech industries. This classification is based on the technological level of each industry (which is estimated by the ratio of the intangible capital costs that come from value-added) and based on the technology, which is used in raw materials and intermediate products in the industry’s production line. This classification is given in Table 3.

Table 3. Classification of Industries Based on Technology Intensity Proposed by the OECD

High-technology industries	**ISIC**	**Medium/high-technology industries**	**ISIC**	**Medium-low-technology industries**	**ISIC**	**Low-technology industries**	**ISIC**
Aircraft and spacecraft	353	Electrical machinery and apparatus	31	Building and repairing of ships and boats	351	Manufacturing, Recycling	36-37
Pharmaceuticals	2423	Motor vehicles, trailers, and semitrailers	34	Rubber and plastics products	25	Wood, pulp, paper, paper products, printing, and publishing	20-22
Office, accounting, and computing machinery	30	Chemicals excluding pharmaceuticals	24	Coke, refined petroleum products and nuclear	23	Food products, beverages	15
Radio, TV and communications equipment	32	Railroad and transport equipment	352	Other non-metallic mineral products	26	Tobacco	16
Medical, precision and optical instruments	33	Machinery and equipment	29	Basic metals and fabricated metal products	27-28	Textiles, textile products	17-18
				Uncategorized vehicle	354	leather and footwear	19

Source: www.oecd.org

Using the table above, ISIC codes are divided into four sections: high-tech industries, medium/high-tech industries, medium/low-tech industries and low-tech industries.

High-tech industries include aircraft and spacecraft, pharmaceuticals, office machinery, radio equipment and medical instruments. The following Fig 5 shows the trend of intangible and physical capital variables in four parts. Section a shows the trend of intangible capital and physical capital changes for the high-tech industries. Section b shows the share of these capitals in production, which indicates a higher share of intangible capital, and we expect intangible capital in these industries to have a high weight to increase TFP. The question that arises is whether ICT has a higher share among the components defined for intangible capital? Section c of the Fig 4 shows that in these industries, the share of non-ICT components, such as research and development, research and laboratory, training, etc., has a higher share. To enhance the growth of TFP, it is expected to increase the cost of NICT.

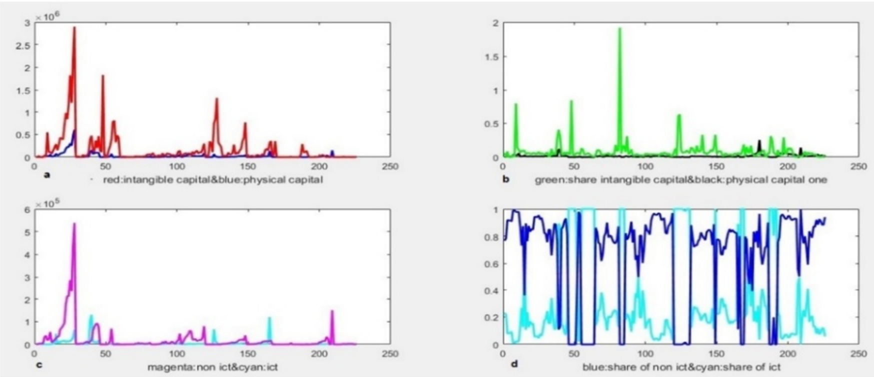

Figure 5. Trend of intangible capital and physical capital variables for four-digit ISIC codes in high-tech industries, **Source:** Authors' own calculations.

In medium/high-tech industries such as machinery and electrical appliances, chemicals except for pharmaceuticals, motor vehicles, trailers and semi-trailers, railway and transportation equipment, and machinery and equipment have a trend like high-tech industries.

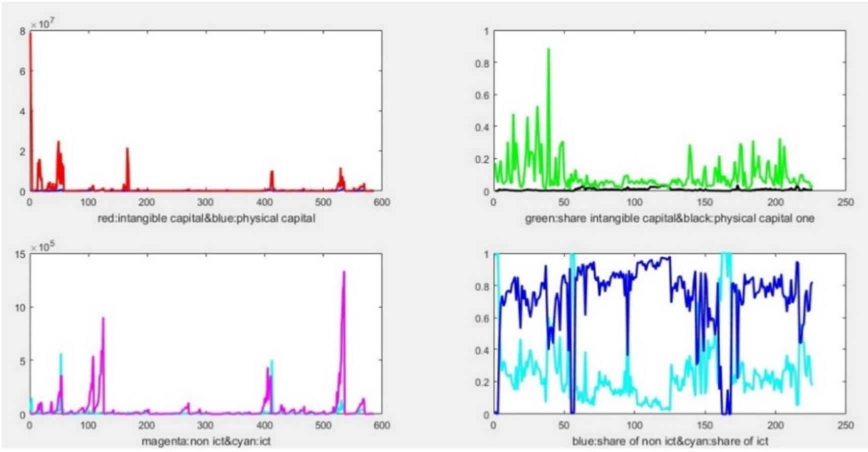

Fig 6. Trend of intangible capital and physical capital variables for four-digit ISIC codes in medium/high-tech industries, **Source:** Authors' own calculations.

In medium/low-tech industries are shipbuilding and repair of ships and boats, rubber and plastic products, coke, refined and nuclear petroleum products, other non-metallic mineral products, base metals and metal products, and uncategorized vehicles. The Figure 6 shows the trend of intangible and physical capital variables in four parts for these industries. As can be seen from the Fig, the share of intangible capital relative to physical capital per production (part b) varies with the two levels studied above. Physical capital has a larger share in these industries. Also, among the components of intangible capital, the share of ICT is higher, which differs from the two high-level charts.

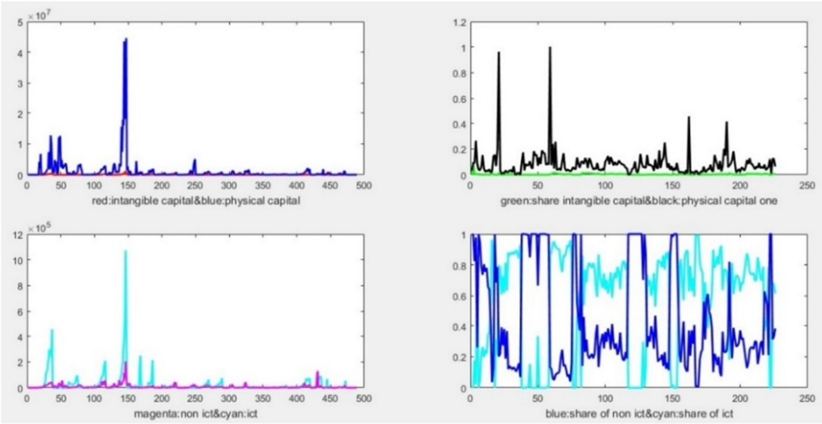

Figure 7. Trend of intangible capital and physical capital variables for four-digit ISIC codes in medium/low-tech industries, **Source:** Authors' own calculations.

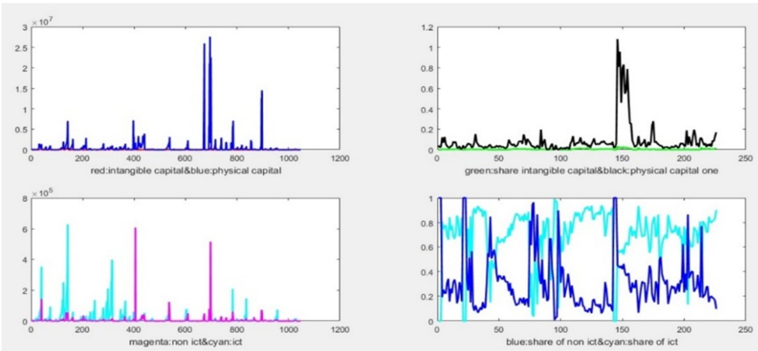

Figure 8 Trend of intangible capital and physical capital variables for four-digit ISIC codes in low-tech industries, **Source:** Authors' own calculations.

The last part of the industry is related to low-tech industries such as manufacturing, recycling, wood, pulp, paper, paper products, printing, food products, beverages, and tobacco. The following Fig shows the trend of intangible and physical capital variables in four parts of these industries. The results are similar to medium/low-tech industries.

The table 4. Shows the estimates of model 2 for industries with different technologies.

Table 4. Intangible Capital and TFP growth: first difference GMM estimation [a].

Dependent Variable: K, L, ICT, NICT

Regressors	**High-technology GMM**	**Medium/high-technology GMM**	**Medium-low-technology RE[a]**	**Low-technology GMM**
LTFP(-1)[b]	0.148 (0.008)	0.610 (0.011)	0.096 (0.026)	0.668 (0.015)
LL	0.071 (0.030)	0.502 (0.046)	0.207 (0.086)	0.625 (0.007)
LK	0.283 (0.053)	0.153 (0.018)	0.573 (0.067)	0.117 (0.006)
NICT	0.309 (0.022)	0.117 (0.025)	0.045 (0.017)	0.026 (0.004)
ICT	0.275 (0.063)	0.085 (0.010)	0.215 (0.079)	0.106 (0.008)
$\bar{R}^2$	-	-	0.8231	-
N[c]	145	501	445	305
Sargan,J-statistic	19.425 (0.195)	40.012 (0.156)	-	28.382 (0.391)
Instrument Rank	20	37	-	32
S.E. of regression	0.905	0.407	-	0.402
Arellano-Bond Serial Correlation Test	AR(1):-3.266 (0.001) AR(2):-0.993 (0.320)	AR(1):-0.002 (0.998) AR(2):0.000 (0.999)	-	AR(1):-0.267 (0.001) AR(2):-1.274 (0.202)

[a] This model does not meet the initial requirement of the GMM model (N> T)

Source: Authors' own calculations.

The results for high-tech and medium/high-technology industries show that ICT weigh less than other components of intangible capital in TFP. For high-tech industries, ICT and other intangible capital components affect TFP by an average of 27% and 31% (respectively). For medium/high-technology industries, ICT and other intangible capital components account for an average of 8.8% and 15% in TFP, respectively. The weight of NICT shows that to increase the productivity of these industries, it is necessary to work on research and development, research and laboratories, brands, and so on.

For medium/low-technology and low-technology industries, models estimation shows intangible capital has a positive and significant effect on TFP. But (unlike high-tech and medium/high-tech industries) the coefficient of this type of capital, unlike physical capital, is not significant. Also in this category, ICT capital weighs much more (21%) compared to other intangible capital components (.04%). The weight of ICT shows that in order to increase the productivity of these two groups of industries, it is necessary to focus on computer software and hardware.

5. Policy Implications and Future Research Agenda

Today, a large portion of studies on economic growth is the accumulation of capital such as human capital, the special role of ICT capital, and new literature in economics called intangible capital (corrado et al., 2005). In Iran, research has been conducted in the field of ICT, R&D, or skilled manpower, but in this study , relying on previous studies,, intangible capital has been measured by taking into account all components (So far, comprehensive studies on intangible capital have not been conducted, including all components). Then, its effect on the total factor productivity summarized based on previous studies. The previous results indicate a positive and significant relationship among them and ICT has a noteworthy role. As the main purpose of this research, using the Pavit method, we have categorized the technology levels as high, medium / high, medium/low, and low. For each of them, we have examined the factors affecting TFP. We have answered the question that which of the components of intangible capital has the greatest impact at these four levels. The results show that at high and medium/high- tech levels, the components of R&D, research and laboratory, skilled labor, have a greater impact on TFP than ICT (for example, in high-tech industries, ICT significantly an average of 27% has an effect on TFP, while the other components have an effect of 31%), and the opposite is estimated for lower levels. To optimize TFP in Iran's manufacturing industries, after dividing them into different levels of technology, in high-tech and medium/high-tech industries, the main focus should be on research and development, research and laboratories, staff-level training, and hiring skilled labor. While for the rest of the industries, the most focus is on ICT, the software and hardware required by that industry is suggested.

References

Arellano, M., & Bond, S. (1991). Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. *The Review of Economic Studies*, *58*(2): 277–297.

Van Ark, B., O' Mahony, M., & Timmer, M. P. (2008). The Productivity Gap between Europe and the United States: Trends and Causes. *Journal of Economic Perspectives, 221*: 25–44.

Balli, H. O., & Sørensen, B. E. (2013). Interaction effects in econometrics. *Empirical Economics*, *45*(1): 583–603.

Bhattacharya, P., & Badri Narayan, R. (2020).Innovation and Firm-level Labor Productivity: A Comparison of Chinese and Indian Manufacturing Based on Enterprise Surveys. *Science, Technology & Society*, 25 (3): 465-481.

Blundell, R., & Bond, S. (1998) Initial Conditions and Moment Restrictions in Dynamic Panel Data Models. *Journal of Econometrics*, *87*(1): 115-143.

Corrado, C., Hulten, Ch., & Sichel, D. (2009). Intangible capital and U.S. economic growth. *Review of Income and Wealth*, *55*(3), 661-685.

---------- (2005). *Measuring capital and technology: an expanded framework*. Chicago: University of Chicago Press.

Corrado, C., Haskel, J., & Iommi (2012). Intangible Capital and Growth in Advanced Economies: Measurement Methods and Comparative Results. *ZA Discussion Papers, Institute for the Study of Labor IZA*, Retrieved from https://www.econstor.eu/bitstream/10419/62563/1/720473268.

Corrado, C., Haskel, J., & Jona-Lasinio, C. (2021). Artificial Intelligence and productivity: an intangible assets approach. *Oxford Review of Economic Policy*, Retrieved from https://spiral.imperial.ac.uk/handle/10044/1/89036.

---------- (2014). Intangibles and Industry Productivity Growth: Evidence from the EU. *IARIW 33rd General Conference Rotterdam, the Netherlands*, Retrieved fromhttp://old.iariw.org/papers/2014/LasinioPaper.

Diewert, W. E. (1993). The early history of price index research Chapter 2 of Essays in Index Number Theory (I). In W. E. Diewert and A. O. Nakamura (Eds.), Retrieved from http://is.muni.cz

Divisia, F. (1926). The Monetary Index and The Theory of Money. "Review of econ. *Polit*, *1*, 49-81.(In French)

Divisia, F.(1925). The monetary index and the theory of money. Review of econ. *Polit*, *XXXIX*, 1121-1151. (In French)

EamaeilySadrabadi F., Jahangard E., Mohammadi T.,& Salem AA.(2021). The effect of intangible capital on the total factor productivity of production in Iran's manufacturing industries. *Quarterly Journal of Quantitative Economics*. Accepted Manuscript Available Online from 25 July 2021.

Hintzmann, C., Masllorens, L., & Ramos Lobo, R. (2021). Intangible Assets and Labor Productivity Growth. *MDPI*, Retrieved from
http://diposit.ub.edu/dspace/bitstream/2445/177614/1/712300.pdf

Haskel, J., & Westlake, S. (2017) .*Capitalism without Capital: The Rise of the Intangible Economy*. Princeton: Princeton University Press.

Jahangard E., Mohammadi T.,Salem AA., EsmaeilySadrabadi F.(2021). Intangible Capital in Industries with Higher Digital Technology Intensity and Total Factor Productivity. *Iranian Journal of Economic Research.*

Jorgenson. D. W., & Timmer, M. P. (2011). Structural change in advanced nations: A new set of stylized facts. *Scandinavian Journal of Economics*, *113*(1): 1–29.

Keungoui K., Bounfour A., Nonnis A., & Özaygen, A. (2021). Measuring ICT externalities and their contribution to productivity: A bilateral trade based approach. *Telecommunications Policy*, *45*(2).

Meinen, G., Verbiest P., & Wolf, P. (1998). Perpetual Inventory Method. *Statistics Netherlands, Department of National Accounts.*

Lall, S. (1992).Technological Capabilities and Industrialization. *World Development*, *20*(2): 165- 186.

Lefophane, M. H., & Kalaba, M. (2021). Estimating effects of ICT intensity on productivity, employment and output in South Africa: an industry-level analysis. *Information Technology for Development.*

Liang, Y. (2021). Intangible capital in U.S. manufacturing, *Economics Letters*, *199*: 109-697.

OECD. (2011). Technology Intensity Definition. Classification of Manufacturing Industries into Categories Based on R&D Intensities. Retrieved from http://www.oecd.org/sti/ind/48350231.

O'Mahony, M., & Timmer. M. P. (2009). Output, Input and productivity measures at the industry level: the EU KLEMS database. *Economic Journal*, *119*(538): 374–403.

Rajan, R., & Zingales, L. (1998). Financial dependence and growth. *American Economic Review*, 88(3): 559–586.

Rico, P., & Cabrer-Borrás, B. (2020). Intangible capital and business productivity. *Economic Research*, *33*: 3034-3048.

Roodman, D. (2009). How to do Xtabond2: An Introduction to Difference and System GMM in Stata. *The Stata Journal*, *9*(1): 86-136.

Schreyer, P., & Pilat, D. (2001). Measuring productivity. *OECD Economic Studies*. *33*: 127–165.

Schultz, E. L., Tan, D. T., & Walsh, K. D. (2010).Endogeneity and the corporate governance - performance relation. *Australian Journal of Management*, *35*(2): 145-163.

Stiroh, K. J. (2002). Information technology and the U.S. productivity revival: What do the industry data say? *American Economic Review*. *92* (5): 1559–1576.

Sawng, Y., Kim, P., & Park, J. (2021). ICT capital and GDP growth: Causality analysis for the case of Korea. *Telecommunications Policy*, *45*(7): 102-157.

Soltanisehat, L., Alizadeh, R., & Mehregan, N. (2019). Research and Development Capital and Productivity Growth in Firms with Different Levels of Technology. *Iranian Economic Review*, *23*(4): 795-818.

Wintoki, M. B., Linck, J. S., & Netter. J. M. (2012). Endogeneity and the dynamics of internal corporate governance. *Journal of Financial Economics*, *105*(3): 581-606.