International Journal of New Political Economy 5(2): 153-179, 2024

Intangible Investment and TFP: Evidence from Small and Medium-Sized Manufacturing in Iran

Forough Esmaeily Sadrabadi[1]*

ARTICLE INFO

Article history:

Date of submission: 15-11-2023

Date of revise: 22-07-2024

Date of acceptance: 27-08-2024

JEL Classification:

O25

O32

O38

O40

Keywords:

CHS

Intangible Investment

Large Industries

Small and Medium Industries

TFP

ABSTRACT

Intangibles refer to capitals like machinery or structures, in the sense that creating them requires foregoing consumption today (investment) to achieve more output in the future. However, unlike machinery or structures, intangibles lack a physical presence. This type of investment has had a significant impact on increasing productivity for industries in Iran. On the other hand, since small and medium industries make up more than 80% of all industries, the effect of this type of investment on the TFP of these industries is of paramount importance. To measure intangible investment, the CHS approach has been used for both groups of different sizes. Therefore, in this study, we have tried to examine the effect of intangible investment on increasing the productivity of these industries. The results for industries with a four-digit ISIC code during the years 1996 to 2021 show that intangible investment not only positively affects the TFP of small and medium enterprises, but also that this effect is significantly larger than that for large enterprises. In general, intangible investment positively affects increasing TFP in all industries. Furthermore, the size of industries and companies has a decisive role on the degree of influence of intangible investment on TFP. Hence, for reaching the highest productivity, it is recommended to focus intangible investment on SMEs.

1. Department of Economics, Faculty of Humanities & Social Sciences, Ardakan University, Ardakan, Iran.
* **Corresponding Author Email Address**: f.esmaeily@ardakan.ac.ir
DOI: https://doi.org/10.48308/jep.5.2.153

1. Introduction

Small and medium-sized enterprises (SMEs) or small and medium-sized businesses (SMBs) are businesses whose personnel and revenue numbers fall under certain limits. The abbreviation "SME" is used by international organizations such as the World Bank, the European Union, the United Nations, and the World Trade Organization (WTO). SMEs currently account for a significant share of GDP. The results of Ayyagari et al. (2007) show that in high-income countries formal SMEs contribute to 50% of GDP (gross domestic product) on average. Furthermore, in many economies the majority of jobs are provided by SMEs. For example, in OECD countries, SMEs with less than 250 employees employ two-thirds of the formal work force (Beck et al., 2008b; Dietrich, 2010). In any given national economy, SMEs sometimes outnumber large companies by a wide margin and employ many more people (Fischer & Reuber, 2000; Olorunshola Odeyemi, 2021). For instance, Australian SMEs makeup 98% of all Australian businesses, produce one-third of the total GDP and employ 4.7 million people. In Chile, in the commercial year 2014, 98.5% of the firms were classified as SMEs (OECD, 2018). In Tunisia, the self-employed workers alone account for about 28% of the total non-farm employment, and firms with fewer than 100 employees account for about 62% of total employment (Rijkerset al., 2014). The United States' SMEs generate half of all U.S. jobs, but only 40% of GDP (CAFC, 2014).

Considered altogether, firm-level productivity depends on a variety of factors, including the enterprise’s size and sector of activity. While larger firms tend to be more productive than smaller ones, productivity in smaller firms may benefit from the intensive use of information and communication technologies (ICT), digital tools, and innovations, particularly in new or younger firms. Obviously, other factors such as human investment (e.g. workforce skills, management skills) also explain differences in productivity across firms, but these factors fall outside the scope of this publication (OECD Compendium of Productivity Indicators, 2021). In Iran, 7 to 9 percent of the GDP depends on the activities of SMEs, and 60 percent of the country's employment is accounted for the activities of such units. Iran's economy is largely determined by government and semi-government institutions and companies, controlling more than ۷0% of the country's economy, especially the activities related to the extraction, refining and trading of crude oil, oil products, and natural gas, providing about 80% of the export income and about 40-50% of the government budget. Currently in Iran, 94% of industrial units include SMEs. These industries account for 43% of industrial jobs. Therefore, identifying the effective factors on increasing productivity in SME is one of the important concepts to evaluate the economic growth of any country. According to the results of the studies by Jahangard et al. (2022), one of the emerging factors with a significant impact on the productivity of industries in Iran is intangible investment.

Haskel (2017) defines investment as what builds up the investment 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 investment, they in fact measured investment in physical goods, plants, and machinery. However, with the advent of the internet in the 1990s, the idea of a new "knowledge economy" emerged based on what economists recognized as the results of research and development (R&D) and the largely nonphysical ideas resulting from it. If this new economy were measured by economists, the valuation of these intangible assets would need to be incorporated into their economic growth models. It is imperative to acknowledge that in various industries, the enhancement of productivity plays a pivotal role in promoting sustained economic growth and serves as a fundamental component of the process of industrialization (Acemoglu & Zilibotti, 2001; Barro & Sala-i-Martin, 1995; Diewert, 2014; El-hadj & Brada, 2009). This paper examines the effect of intangible investment on Total Factor Productivity (TFP) in SMEs and answers the question whether the size of enterprises affects increasing productivity through the channel of increasing intangible investment.

According to the definition of the Central Bank of Iran, companies with less than 50 employees are classified as SMEs. The statistics and information of the Statistical Center of Iran show that in the last few years, 70% of the total production of the industrial sector has been averagely allocated to SMEs. Therefore, these companies can play a significant role in increasing productivity (the focus of the present research).

The current paper is aimed at investigating the effect of intangible investment on the productivity of SMEs using the CHS approach and our studies already performed in the field of tangible investment measurement. It answers the question, is the size of the companies important in the impact of this type of investment?. To measure intangible investment in Iran, we follow the approach of Corrado et al., 2005, 2006 (abbreviated as CHS hereafter), those classifying 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, with the latter referring to, for example, mineral exploitation, copyright and license costs, other product development, design, and research expenses. Finally, economic competencies include brand equity, firm-specific human investment, and organizational structure (Jahangard et al., 2021, 2021).Then, according to the definition of SMEs by Statistical Center of Iran, the effect of this type of investment on the TFP of these types of companies is investigated. Subsequently, the results are compared with those of large companies and the impact of intangible investment on SMEs is investigated. It is worth noting that the studied data for measuring intangible investment are four-digit ISIC codes for small and medium Iranian industries during the years 1996 to 2021 and the model used is the panel by GMM method.

This paper consists of five sections. In the next section, previous studies in the field of measuring intangible investment, the relationship between intangible investment and TFP, and the SMEs will be reviewed. Next, the theoretical points of the subject will be presented. Then, intangible investment following the methodology developed by Corrado et al. (2005; 2006) will be estimated, its effect on TFP growth for SMEs will be examined and compared with large industries. The last section summarizes the results and their policy implications and discusses future tasks.

2. Literature Review

Jahangard et al. (2021, 2023) have measured intangible investment. In this study, the CHS approach (a comprehensive and accepted approach used in most important studies) has been employed to measure intangible investment (Corrado, Hulten, and Sichel, 2005). In order to find the answers to the research questions and approach its hypotheses, the study period of 1996-2018 for industrial workshops of ten employees and above, using the four-digit ISIC code (ISIC) is used. The results indicate that intangible investment positively and significantly affect TFP. Additionally, among the components, Information and Communication Technology (ICT) has a more prominent role on the TFP variable. The other study examines all the factors (playing role in measuring intangible investment) on the growth of TFP at different levels of technology (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 reveal 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.

According to Albis Salas et al. (2023), investing in R&D positively affects innovation in both SMEs and larger firms. However, the effect on productivity is significantly higher for SMEs. Besides, evidence suggests that the innovation performance of SMEs and larger firms is influenced by co-evolution among the firm's resources and capabilities, knowledge flows with external organizations, access to funding, and knowledge appropriability conditions. However, highly qualified personnel, internal and commercial sources of funding, and market knowledge sourcing are crucial for innovation in SMEs. These conclusions are particularly relevant for the design of industrial and innovation policies in developing economies, where innovation is a prerequisite for catching up and economic advancement.

In the era of the digital economy, the relationship between digital transformation and total factor productivity at the firm level has incalculable repercussions for businesses seeking to sustain high-quality growth. Furthermore, it is crucial to enhance the total factor productivity of a company as it contributes to the accomplishment of sustainable development. Consequently, Cong Dinh et al. (2023) investigates the effects of firm-level digital technology on TFP levels using Vietnamese SMEs data from 2015 to 2019. Based on their empirical findings, digital technology positively affects firm productivity. However, the digital technology productivity premium varies across businesses (Cong Dinh et al., 2023).

Jianguo and Qamruzzaman assess SMEs performance for the period of 2005-2014. Their study measures productivity using Malmquist Productivity Index (MPI) with one output and three inputs. They run regression analysis to identify residual by comparing expected output and an actual output with available inputs. Study result revealed that productivity index (MALM = 1) remained constant, but technical efficiency increased from 2010 to 2014, however overall efficiency declined by 2.6%. The residual analysis revealed no significant deviation between expecting output and actual output using available inputs. This research outcome give a glimpse about overall SME performance, which will induce researchers to go further in-depth analysis for bringing more insight for SME development (Jianguo & Qamruzzaman, 2017). Chen and Lee show that the TFP growth of European micro, small, and medium-sized enterprises (SMEs) diverged from large firms after the global financial crisis. The average post-crisis TFP growth of micro, small, and medium-sized enterprises was, 1.1, 2.9, and 5.4% points lower than that of large firms, respectively. This SME productivity gap is larger for firms with more severe credit supply shocks. The gap is partially attributable to a larger post-crisis reduction in intangible investment at SMEs compared to that at large firms. Horseraces suggest that SME indicators are more robust and more powerful predictors of post-crisis TFP growth than other indicators (Chen & Lee, 2023). The study for Spain SMEs shows that the introduction of process innovations yields an extra productivity growth, and that the life span of this extra productivity growth lasts for only one period (Manez et al., 2013).

The study by Majid et al. (2021) measures and decomposes the SMEs' TFP in the agricultural sector across 23 regencies/cities in Aceh province, Indonesia during the 2015-2019 period. Using Data Envelopment Analysis (DEA), the study found a low level of SMEs' productivity during the study period. The SMEs in Aceh province recorded different levels of TFP. Overall, the SMEs' TFP has slightly declined, contributed mainly by an increase in efficiency level and a decline in the technical efficiency change. These findings showed the importance of adopting advanced agricultural-related technologies and implementing good SMEs' governance principles to further improve SMEs' TFP. Ultimately, the government must prioritize promoting non-productive SMEs across the 23 regencies/districts in the province through offering sufficient financial aids and conducting professional managerial training programs.

3. Materials and methods

Pursuant to Cobb-Douglas production function, we have the following equation:

$$Y_{it} = A_i K_{it}^{\beta 1} L_{it}^{\beta 2} \quad (1)$$

where Y is value added; K refers to the stock of investment; L shows labor units; and A stands for the efficiency level. The relationship between intangible investment and TFP may be written as:

$$Y_{it} = A_{it} F_{it}(L_{it}, K_{it}, R_{it}) \quad (2)$$

Y, A, L, and K have already been defined. The stock of intangibles investment is denoted by R_{it}[1]. We get the differential Equation 3:

$$\Delta lnY_{it} = \varepsilon_{it}^{L}\,\Delta lnL_{it} + \varepsilon_{it}^{K}\Delta lnK_{it} + \varepsilon_{it}^{R}\Delta lnR_{it} + \Delta lnA_{it} \tag{3}$$

So that ε^{X} represents the production elasticity of factor X, basically different according to input, industry, and time. To empirically examine the role of intangibles as growth drivers, existing literature is used and this is done in two stages. First, consider the condition of ϵ. For a company with the lowest cost, we have:

$$\varepsilon_{it}^{X} = S_{it}^{X}\,, X = L, K, R \tag{4}$$

where S is the share of payments of this invoice in relation to value added. Therefore, this equation simply expresses the first order condition of a firm in terms of production elasticity. Now suppose that a firm can benefit from K, L, or R variables in other firms, industries, or countries. Therefore, as Griliches (1992) pointed out, the industry elasticity ΔlnR in ΔlnY is a combination of input and output elasticity. Then, we can follow Stiroh (2002) and have:

$$\varepsilon_{it}^{X} = s_{it}^{X} + d_{it}^{X}\,, X = L, K, R \tag{5}$$

which shows that the production elasticities of the factors are equal to the weight of the factors. Moreover, there is flexibility of deviation from the weight of the factors due to spillovers. All this can be shown by substituting in Equation 4:

$$\Delta ln\, Y_{i,t} = \left(s^{L}{}_{i,t} + d^{L}{}_{i.t}\right)\Delta lnL_{i,t} + \left(s^{K}{}_{i,t} + d^{K}{}_{i,t}\right)\Delta lnk_{i,t} + \left(s^{R}{}_{i,t} + d^{R}{}_{i,t}\right)\Delta lnR_{i,t} + \Delta lnA_{i,t} \tag{6}$$

To model for TFP, the studies of Caves, Christensen, and Diewert (1982) have been used, and the index is constructed with the translog production function as follows:

$$\Delta lnTFP_{it} = d_{it}^{L}\Delta lnL_{it} + d_{it}^{K}\Delta lnK_{it} + d_{it}^{R}\Delta lnR_{it} + \Delta lnA_{it} \tag{7}$$

1. 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)(Appendix B)

4. Empirical results and impulse-response functions analysis

In this part, first, the method of measuring intangible investment is examined. Then, the position of large, medium, and small industries and their share in the total production of the industry sector is examined. In addition, the share of intangible investment for each industry is examined. Finally, the estimation of the model and presentation of the results will be discussed.

4.1. Measuring the intangible investment

CHS approach has been used to measure intangible investment. Previous studies have been conducted to investigate intangible investment for all industries with ten employees and above. In this paper, we have used the method of measuring this study in accordance with the CHS approach (Appendix A).

4.2. The position of SMEs in Iran

According to the studies of the Statistical Center of Iran, based on worker classes in 2021 and 2019, the distribution of industrial workshops with ten or more workers is as follows:

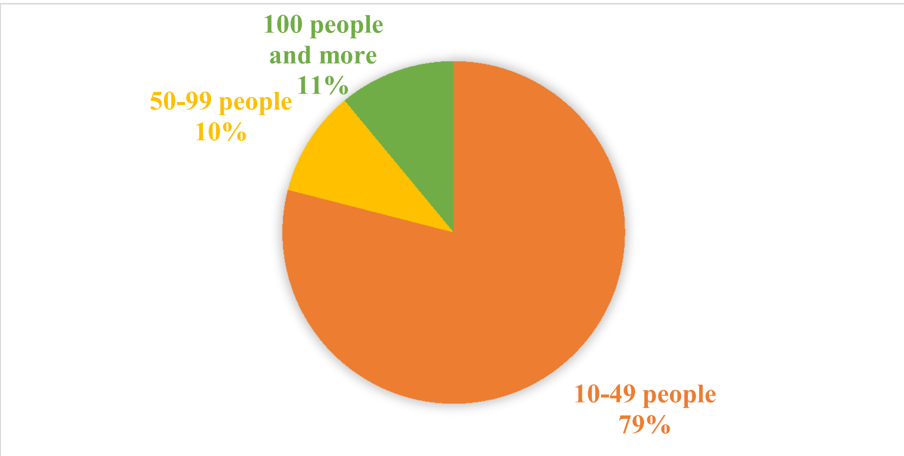

Fig. 1: Distribution of industrial workshops 2021
Source: Statistical Center of Iran

Pie chart 1 shows that in 2021, the share of industries with less than 50 people compared to all Iranian industries has a share equal to 79%, revealing the high importance of this type of industry compared to all other industries. Therefore, investigating the factors affecting the productivity of this type of industry can lead to the productivity of the entire production factors.

The results of studies by Jahangard et al. (2022) show that intangible investment, like physical investment and labor, have a significant contribution to increasing TFP. Therefore, in the present study, it is aimed at investigating the effect of intangible investment on TFP of SMEs industries. Considering the high share of these industries in the entire industry, it is not unexpected that this investment variable has a significant contribution. Fig. 2 consists of three parts. The first part shows the amount of production and intangible investment in large industries according to the ISIC codes of 2021 (The horizontal axis represents the four-digit ISIC codes of Iran's industries while the vertical axis shows the amount of intangible production and investment).

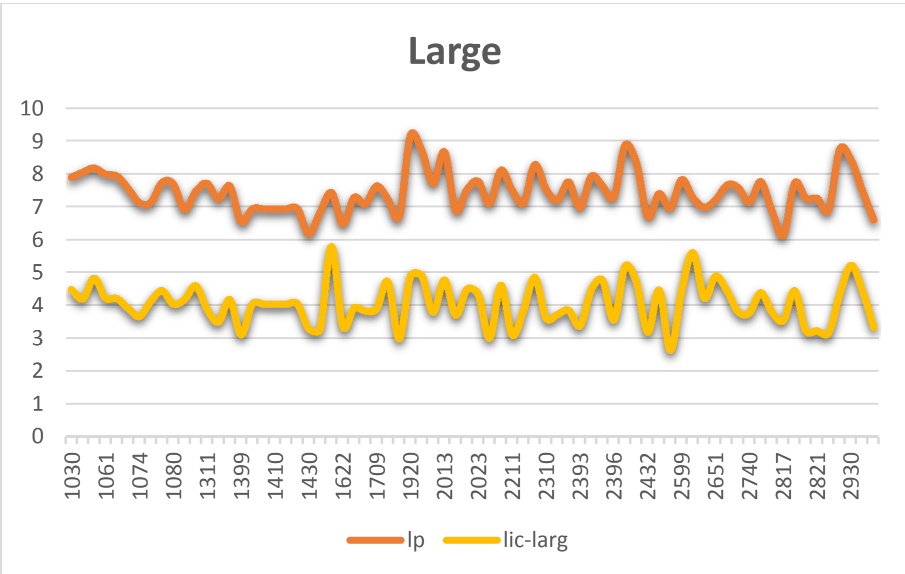

Fig 2-a. The amount of production and intangible investment in large industries according to the ISIC codes of 2021, Source: Authors' own calculation

As shown in the figure, a significant share of production is allocated to intangible investment, confirming the previous studies depending on the positive and significant impact of intangible investment on TFP in industries.

In the second part, a graph is displayed for SMEs industries. As in large industries, a significant share of production is allocated to intangible investment, emphasizing the importance of investigating the factors affecting the productivity of these types of industries.

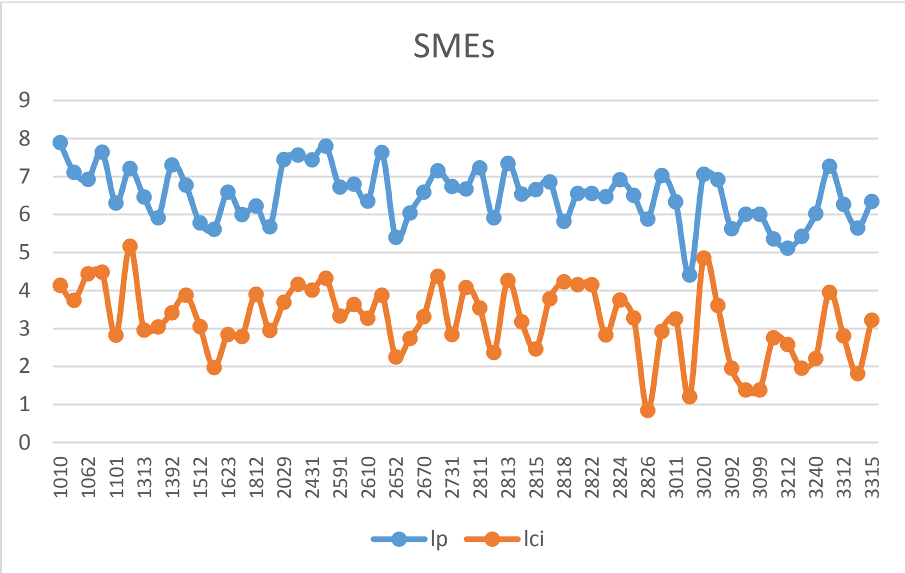

Fig. 2-b. The amount of production and intangible investment in SME industries according to the ISIC codes of 2021, Source: Authors' own calculation

In the third part, it is focused on the share of intangible investment from the total production in both groups of industries. As observed in the figure, the share of intangible investment in SMEs is higher than in large industries, proposing that SMEs are one of the factors influencing production, with an investment share more than that of large industries.

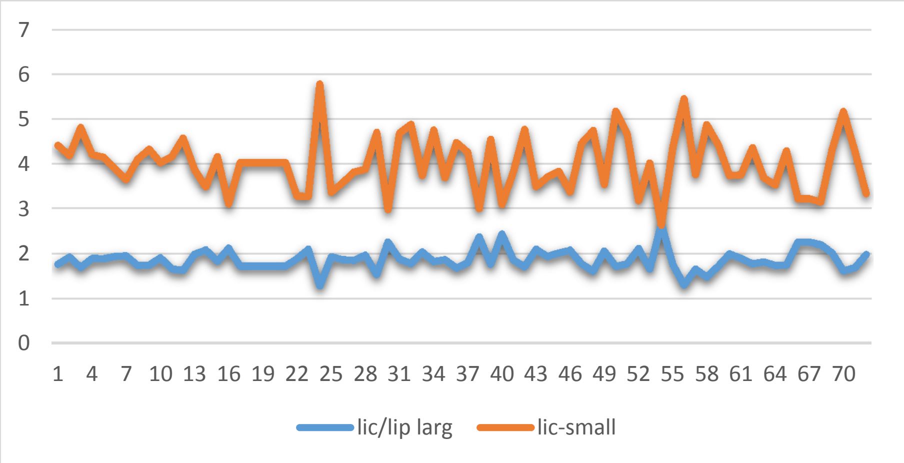

Fig. 3-c. The share of intangible investment in Large and SME industries according to the ISIC codes of 2021, Source: Authors' own calculation

4.3. Econometrics Results

Productivity is the efficiency of production of goods or services expressed by some measures. Measurements of productivity are often expressed as a ratio of an aggregate output to a single input or an aggregate input used in a production process, i.e. output per unit of input, typically over a specific period (Kaliski, 2001). For Estimating TFP in Equation 7, panel data for 134 four-digit classification codes of economic activities during the years 1997-2021 have been used. The proposed models for them are fixed effects model and random effects model. Nevertheless, since the TFP dependent variable appears with an interval on the right side, the most suitable model proposed is the dynamic pattern in panel data (Appendix c).

Prior to entering into the estimation of the model, the stationarity of the studied variables has been investigated. To this end, Levin, Lin, and Chu (LLC), Im, Pesaran and Shin (IPS) and Fisher (ADF) tests have been used to check the model variables' stationarity. Table 1 shows the unit root test of each of the examined variables.

Table 5: The results of the unit root test of model variables*

Tests						Variable
ADF		IPS		LLC		
First order difference	Level	First order difference	Level	First order difference	Level	
819.25 (0.0000)	178.61 (1.0000)	-17.69 (0.0000)	6.55 (1.0000)	-16.16 (0.0000)	-4.79 (0.0000)	TFP
1103.64 (0.0000)	186.86 (0.9999)	-25.00 (0.0000)	3.19 (0.9993)	-21.27 (0.0000)	-1.89 (0.0294)	LPhysical Investment
955.11 (0.0000)	365.62 (0.0000)	-20.91 (0.0000)	-3.56 (0.0002)	-18.36 (0.0000)	-13.44 (0.0000)	Lintangible Investment
662.97 (0.0000)	277.93 (0.2660)	-13.52 (0.0000)	-0.72 (0.2357)	-11.54 (0.0000)	-4.53 (0.0000)	LLabor

* L refers to the logarithm

Source: Authors' own calculations

As observed, due to the instability of most variables regardless of the time trend and differentiation, and in some of them with the first order difference at the 99% level, the null hypothesis of the unit root test is rejected. Therefore, it is ensured that all the variables used in the model are static. In this part, we have estimated the Equation 7 with GMM model. We estimated the model for three groups of small, medium, and large industries based on the size of the companies and the Statistical Center of Iran. The results are as follows:

Table 2. Intangible investment growth and TFP: SME industries

Variable	(Coefficient)	(t-Statistic)	(Std. Error)	Prob.
LTFP(-1)	0.323	65.2890	0.00496	0.0000
L Intangible Investment	0.448	156.77	0.002	0.0000
L Physical Investment	0/247	64.35	0.003	0.0000
L Labor	0.292	25.56	0.011	0.0000
Sargan, J-statistic	54.347 (0.538)		Number of observations (N)	876
S.E. of regression	0.591		Instrument Rank	57
Arellano-Bond Serial Correlation Test :				
AR(1)		-3.481 (0.0001)	AR(2)	0.942 (0.2573)

Source: Authors' own calculations

As Table 2 shows, intangible investment is one of the variables affecting productivity in SMEs. The results show that compared to the rest of the components, intangible investment has the greatest impact on TFP with a coefficient of 0.44 for SMEs. Sargan Test and J-statistic and Arellano-Bond Serial Correlation Test at the end of the table show the consistency of the GMM estimator (The explanation of GMM and the tests performed are detailed in Appendix C).

Table 3. Intangible investment growth and TFP: Large industries

Variable	Coefficient	t-Statistic	Std. Error	Prob.
LTFP(-1)	0.244	57.1342	0.0042	0.0000
LTFP(-2)	0.1574	44.7189	0.0038	0.0000
L Intangible Investment	0.362	151.81	0.006	0.0000
L Physical Investment	0.209	78.841	0.0017	0.0000
L Labor	0.356	44.67	0.005	0.0000
Sargan, J-statistic	50.005 (0.296)	Number of observations (N)		790
Instrument Rank	56	S.E. of regression	0.451	
	Arellano-Bond Serial Correlation Test			
	1.902 (0.6007)	AR(2)	-1.910 (0/004)	AR(1)

Source: Authors' own calculations

Table 3 states that in large industries, as in other industries, intangible investment play a prominent role in TFP. In this type of industries, this share is equal to 0.36. Like intangible investment, investment and labor positively and significantly affect TFP. (It is noteworthy that the capital inventory (both physical and intangible is used in the production function, the calculation method of which is given in Appendix B). According to the results, in all industries with different sizes, the intangible investment coefficient is larger than the rest of the components. The effect of intangible investment to increase TFP is evident in all industries, in line with the results of previous studies. The results indicate that the share of the impact of SME industries’ intangible investment on TFP is greater than the rest of the industries (0.44 compared to 0.3۶), suggesting that besides the positive and significant impact of this intangible investment on all industries and the obvious focus on this type of investment, small industries have the greatest effect in reaching the most optimal state of TFP.

5. Conclusion and policy implications

The studies of the Statistical Center of Iran show that small industries account for a high percentage of the total industry in Iran's economy. Hence, it is important to examine the factors affecting this type of industry. One of the key factors in any industry is TFP. Studies in different countries show that in addition to effective factors like physical investment and labor, being effective on TFP until now, another important factor called intangible investment not only is effective, but it significantly contributes to other variables (Rico, Bhattacharya, and Rath, 2020; Liang, 2021; Hintzmann, Masllorens, and Ramos Lobo, 2021; Corrado, Hulten, and Sichel, 2009; Corrado, Haskel, and Jona-Iommi, 2013). In this study, we answered the question, which of the small, medium, and large industries have more weight in the increase of TFP. The results showed that intangible investment positively and significantly affects TFP and confirms the previous studies. Nevertheless, since the companies’ size is a very important component, in this study, its effect on the amount of intangible investment effect on TFP was discussed. The high weight of intangible investment in SMEs compared to other industries (in terms of size) indicates the significant contribution of SMEs in reaching the optimal point of TFP through increasing intangible investment. Therefore, in order for industries to have higher productivity, they should first pay more focus on intangible investment, but not all industries of different sizes need to invest the same amount on this type of investment. Small industries with a larger coefficient may focus most on this type of transitory investment, i.e. the number of workers is not as important as the hiring of specialized and professional forces to achieve the highest productivity, for example. Small industries should expand research and development, advertising, information and communication technology, and the components involved in intangible investment to enhance the productivity growth of industries in the macro state.

Accordingly, due to the very high share of SMEs in industries, it is suggested to expand the intangible investment factor to reach the optimal TFP. I.e. small industries can achieve higher TFP by employing a skilled and expert workforce, increasing research and development in the field of their industry, using ICT and using new and emerging technologies. Besides, policymakers are advised to support this type of industries to raise the total productivity by means of high and emerging technologies and increasing the factors involved in intangible investment. Because small and medium industries, especially small ones cannot increase intangible investment compared to large industries. It is proposed to create small industrial clusters with regard to the expansion of communication networks and the creation of knowledge-based companies in order to separate intangible investments on small industries and increase their productivity. For instance, different industries can outsource innovations and ideas related to technology updated every day to small industries. In the continuation of this study, it is suggested that each of the small industries is a specialist in one of the influencing factors of intangible investment for other industries. In this way, for example, people working in the wood industry can hand over new designs with new software to other companies. This same concept of industrial clusters, which can be implemented with the expansion of the Internet network, can be a very strong way to increase TFP in industries.

Funding

The present study received no financial support from any organization.

Authors' Contributions

All authors had equal contribution in preparing this paper.

Conflicts of Interest

The authors declare no conflict of interest

References

Acemoglu, D., Dorn, D., Hanson, G. H., & Price, B. (2014).Return of the Solow paradox? IT, productivity, andemployment in US manufacturing. *American EconomicReview*, 104(5), 394-399. doi: https://doi.org/10.1257/aer.104.5.394

Acemoglu, D., & Zilibotti, F. (2001). Productivity differences.*The Quarterly Journal of Economics,*116(2), 563-606. doi:https://doi.org/10.1162/00335530151144104

Albis Salas, N., Mora Holguin, H., Lucio-Arias, D., Sánchez, E.C. ,& Villarreal, N. (2023). Innovation and productivity in small and medium-sized enterprises: evidence from the Colombian manufacturing sector. *Journal of Small Business and Enterprise Development*, 30(5), 1011-1034. Doi: https://doi.org/10.1108/JSBED-12-2021-0502.

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. https://doi.org/10.2307/2297968.

Arellano, M.,& Bover, O. (1995) Another Look at the Instrumental Variable Estimation of Error-Component Models. *Journal of Econometrics,* 68(1), 29-52. http://dx.doi.org/10.1016/0304-4076(94)01642-D

Anderson, T.W., & Hsiao, CH. (1981). Estimation of Dynamic Models with Error Components.*Journal of the American Statistical Association*, 76(375), 598-606.Doi: https://doi.org/10.2307/2287517.

Ayyagari, M., Beck, T., & Demirgüç-Kunt, A. (2007). Small and Medium Enterprises across the Globe. *Small Business Economics*, 29(4), 415-434. http://www.jstor.org/stable/40229581.

Antoldi, F., Cerrato, D., & Depperu,D.(2012). *Export Consortia in*

Developing Countries: Successful Management of Cooperation among SMEs. Berlin: Springer Science & Business Media. ISBN 9783642248788.

Aga, G., Francis, D.C., & Rodriguez Meza,J.(2015). SMEs, Age, and Jobs: A Review of the Literature, Metrics, and Evidence. *Policy Research Working*, (7493). World Bank, Washington, DC. http://hdl.handle.net/10986/23455.

Baltagi, B.H. (2005). *Econometric Analysis of Panel Data*. Springer Texts in Business and conomics.ISBN:978-3-030-53953-5.

Barro, R. J., & Sala-i-Martin, X. (1995). Economic Growth.McGraw-Hill. New York.

Beck, T., Demirgüç-Kunt, A., & Peria, M. (2008). Bank Financing for SMEs around the World: Drivers, Obstacles. *Business Models, and Lending Practices*. Policy Research Working Paper 4785. World Bank, Washington, DC.

Bell, S. (2015). Small and medium enterprises (SMEs) finance. Available in: http://www.worldbank.org/en/topic/financialsector/brief/smes-finance.

Chen, S., & Lee, D. (2023). Small and vulnerable: SME productivity in the great productivity slowdown. *Journal of Financial Economics*.147(1), 49-74.

Doi: https://doi.org/10.1016/j.jfineco.2021.09.007

Cong Dinh, KH., Quang Ngo , TH.,& Van Nguyen, D.(2023). Firm-level digital technology and Total Factor Productivity in a developing country: Evidence from panel data in Vietnam. *Cuadernos de Economía*, 46(130), 41-55.

Corrado, C., Hulten,C.,& Sichel ,D .(2005).Measuring investment and technology: an expanded framework. *National Bureau of Economic Research*, University of Chicago Press.

Corrado, C., Hulten, C., & Sichel, D. (2009) .Intangible investment and U.S. economic growth. *Review of Income and Wealth*, 55 (3). Doi:10.1111/j.1475-4991.2009.00343.x.

Corrado, C., Haskel, J., Jona-Lasinio,C.,&Iommi,M.(2012).Intangible Investment and Growth in Advanced Economies: Measurement Methods and Comparative Results. ZA Discussion Papers.*Institute for the Study of Labor IZA*.Bonn. 6733.

Corrado, C., Haskel, J., &Jona-Lasinio, C. (2014).Intangibles and Industry Productivity Growth: Evidence from the EU.*IARIW 33rdGeneral ConferenceRotterdam*.24-30.

Corrado, C., Haskel, J., & Jona-Lasinio, C. (2021).Artificial Inteligence and productivity:an intangible assets approach. *Oxford Review of Economic Policy*, 37(3), 435-458. Doi:10.1093/oxrep/grab018.

Cueto, L., Frisnedi, A., Collera, R., Batac, K., & Agaton, C. (2021). Digital Innovations in MSMEs during Economic Disruptions: Experiences and Challenges of Young Entrepreneurs. *AdministrativeSciences*, 12(1),1-25. Doi:10.3390/admsci12010008. ISSN 2076-3387.

Dietrich, A. (2010). Explaining Loan Rate Differentials between Small and Large Companies: Evidence from Switzerland. *Small Business Economics*, 34(8), 481-494. DOI: 10.1007/s11187-010-9273-8

Diewert, W. E. (2014). US TFP growth and the contribution of changes in export and import prices to real income growth. Journal of Productivity Analysis. 41 (1), 19-39.Doi: https://doi.org/10.1007/s11123-013-0369-4

El-hadj, M. B., & Brada, J. C. (2009). Total factor productivity growth, structural change and convergence in the new members of the European Union. *Comparative economic studies*, 51(4), 421-446.Doi: https://doi.org/10.1057/ces.2009.8

EsmaeilySadrabadi F., & Jahangard, E. (2021). Total Factor Productivity and Intangible Investment in Different Levels of Technology: A Case Study of Iranian Manufacturing Industries. *International Journal of New Political Economy*, 3(2), 27-50.

Doi: https://doi.org/10.52547/jep.3.2.27.

EamaeilySadrabadi F., Jahangard E., Mohammadi T., & Salem AA. (2021). The effect of intangible investment on the total factor productivity of production in Iran's manufacturing industries. *Quarterly Journal of Quantitative Economics*, 20(3), 78-109. (In Persian). https://doi.org/10.22055/jqe.2021.37224.2363

EsmaeilySadrabadi, F., Jahangard, E., Mohammadi, T., & Salem, A.A. (2023). Intangible Investment in Industries with Higher Digital Technology Intensity and Total Factor Productivity. *Iranian Journal of Economic Research*. 28(94), 7-46. (In Persian)

Doi: https://doi.org/10.22054/ijer.2021.60583.969

Gibson, T., & van der Vaart, H. J. (2008). Defining SMEs: a less imperfect way of defining small and medium enterprises in developing countries. Brooking global economy and development.

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

Hintzmann, C., Lladós Masllorens, J., & Ramos, R. (2021). Intangible Assets and Labor Productivity Growth, *Economies*, 9(2), 1-21. Doi:10.7238/in3wps.v0i0. 2711.

Jianguo, W., & Qamruzzaman, Md. (2017). An Assessment of Total Factor Productivity (TFP) of SME Business in Bangladesh using DEA-based Malmquist Productivity Index (MPI). *ABC Journal of Advanced Research*, 6(1), 31-40.doi: http://dx.doi.org/10.18034/abcjar.v6i1.68

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

Fischer, E, & Reuber, R. (2000). *Industrial Clusters and SME Promotion in Developing Countries*. Commonwealth Secretariat. ISBN 9780850926484.

Majid, M.S.A., Faisal, F., Fahlevi,H., Azhari,A., & Juliansyah, H. (2021). Decomposing total factor productivity of SMEs in agricultural sector in Aceh, Indonesia. IOP Conference Series: Earth and Environmental Science, 951. Doi: 10.1088/1755-1315/951/1/012051.

Griliches, Z. (1979). Issues in assessing the contribution of research and development to productivity growth.*Bell Journal of economics*. 10(1), 92-116.

Doi: https://doi.org/10.2307/3003321

Griliches, Z. (1991).The Search for R&D Spillovers. *NBER Working Paper*, 3768. Doi: 10.3386/w3768.

Griliches, Z (1992). *Output Measurement in the Service Sectors*. National Bureauof Economic research, University of Chicago Press. Retrieved from https://press.uchicago.edu/ucp/books/book/chicago/O/bo3624384.html

Griliches, Z., & Mairesse, J. (1995).Production Function:The Search For The Identification.*National Burea Of Economic Research*,(w5067). Retrieved from https://ssrn.com/abstract=225845

Kaliski, B. S. (2001). *Encyclopedia of busine and finance*. Macmillan Reference USA.New York. ISBN:0-02-866061-7.

Matyas, L., & Sevestre, P. (2008). *The Econometrics of Panel Data*. Fundamentals and Recent Developments in Theory and Practice. ISBN: 978-3-540-75889-1.

Manez, J.A., Rochina-Barrachina, M.E., Sanchis, A., & Sanchis, J.A. (2013). Do process innovations boost SMEs productivity growth? *Empirical Economics* (44), 1373–1405. https://doi.org/10.1007/s00181-012-0571-7.

OECD Publishing. (2018). Financing SMEs and Entrepreneurs.155– 173. ISBN 9789264249462. Retrieved from Doi:10.1787/fin_sme_ent-2016-11-en.

Olorunshola, D., & Odeyemi, T. (2021). Virtue or vice? Public policies and Nigerian entrepreneurial venture performance. J*ournal of Small Business and Enterprise Development*, 30(1), 100–119. doi:10.1108/JSBED-07-2021-0279.

Petrakis, P.E., & Kostis, P.C. (2012). The Role of Knowledge and Trust in SMEs. *Journal of the Knowledge Economy*, 6, 105-124. Retrieved from https://link.springer.com/article/10.1007/s13132-012-0115-6.

Rico, P., & Cabrer-Borrás, B. (2020). Intangible capital and business productivity. *Economic Research-Ekonomska Istraživanja*, 33, 3034- 3048. DOI: https://doi.org/10.1080/1331677X.2019.1699139.

Rijkers, B., Arouri, H., Freund, C, & Nucifora, A. (2014). Which firms create the most jobs in developing countries? *Labour Economics*, 31, 84–102. DOI: 10.1016/j.labeco.2014.10.003

Stiroh, K.J. (2002). Information Technology and the U.S. Productivity Revival: What Do the Industry Data Say? *The American Economic Review*. 92(5), 1559-1576. DOI: 10.1257/000282802762024638.

https://www.amar.org.ir/

https://www.cbi.ir/

Appendix A: Intangible Investment

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

Table 4. 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[a]
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 1.computer software and 2.computer database. The innovative property contains 3.science and engineering research and development, 4.copyright and licenses for the development of entertainment and art, and 5.other costs of product development, design, and research. Economic competencies include 6.equity, 7.company-specific human capital, and 8.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 paper, he pointed out that he had used the CHS approach to calculate intangible capital. There have been many studies on the intangible capital's impact on productivity in the world. Van Ark and Timmer (2008) showed that 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 compared the results between the Chinese and Indian manufacturing sectors. They found out 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 revealed that all the three different categories (CHS approach) of intangible assets contribute to labor productivity growth. In particular, intangible assets related to economic competencies were identified as the main drivers.

The ICT factors' impact on the development of economic and economically driven processes is indisputable. ICT is a key component in measuring intangible capital; thus, 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. Their findings suggest that industries with higher ICT intensity experience greater and more significant growth effects. 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 South Korea's GDP growth. The results revealed that ICT and GDP growth's effects were positive.

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, revealing that R&D expenditures in high-tech and medium/high-tech industries positively affect 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, realizing 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.

Appendix B: 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:

$$Y_{it} = A_i K_{it}^{\beta_1} L_{it}^{\beta_2} e^{it} \tag{8}$$

where Y is value added; K refers to the stock of capital; L shows labor units; A stands for the efficiency level; e represents an error term; i = 1, 2, …, N = 135 four-digit ISIC codes, and t = 1, 2,…, T = 26 (for the period of 1996–2021).

The production function is estimated in a log-linear form within a lag framework. The model of empirical panel is specified as follows:

$$LTFP_{it} = \alpha_i + \beta_1 \Delta lnL_{i,t} + \beta_2 \Delta lnK_{i,t} + \beta_3 \Delta lnR_{i,t} + \beta_4 LTFP_{i,t-1} + u_{it} \quad (9)$$

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

The Divigia method with the Trenquist approximation is the appropriate method for measuring TFP in Iran, suitable for discrete statistical data, since the contributions of the production factors are different from one activity to another and change from year to year. It considers changes in the quality of production factors. In the current research, a production function has been used to calculate TFP, where production Y is a function of three inputs labor L, physical investment inventory K, and intangible investment inventory I, and the calculation formula of TFP is as follows:

$$TFP = \frac{Y_t}{K_t^{\alpha} L_t^{\beta} I_t^{1-\alpha-\beta}} \quad (10)$$

where Y is the output value, K shows the value of investment services, L represents the number of employees and I stands for the value of intangible investment. Besides, β = (employee compensation/total production) and $1 - \alpha - \beta$ is the production elasticity of intangible investment that is equal to dividing the payment for intangible investment by total output. Moreover, α is obtained by subtracting the above two tensions.

In Equation 7, the two variables of physical investment inventory and intangible investment inventory are considered independent variables of the productivity of the total production factors, and the following method is employed to calculate its inventory. Accumulation data of physical and intangible investment is obtained by the formula below:

$$INT_{it} = (1 - \delta_i)INT_{it-1} + \frac{intangible_{it}}{P_t} \quad (11)$$

so that INT_{it} is the accumulation of intangible investment for the four-digit economic activity classification code *i* at time *t*. The intangible variable *t* is the intangible investment variable for the classification code of the four-digit economic activity rank i at time *t*. A bunch of studies have been conducted on how to calculate the depreciation rate. In this research, the study by Amini (2014) was used, where δ_i is different for each code.

Appendix C: GMM

Since the dependent variable in the research model appears as an interval on the right side of the equation, we are faced with a dynamic panel data pattern. The general form of a dynamic pattern in panel data is as follows:

$$Y_{it} = \alpha Y_{it-1} + \beta X_{it} + \mu_i + \varepsilon_{it} \tag{12}$$

where: Y_{it} is the dependent variable, X_{it} represents the vector of independent variables also used as instrumental variables, μ_i shows the error factor related to sections and ε_{it} refers to the error factor of the *i* section at time *t*. When in the panel data model, the dependent variable appears as an interval on the right side, ordinary least squares (OLS) estimators are no longer compatible (Arellano and Bond, 1991), and one must resort to the two-stage least squares (2SLS) method of Anderson and Hsiao (1981) or Generalized Method of Moments (GMM) of Araleno and Bond (1991). According to Matyas and Sevestre (2008), the 2SLS estimation may give large variances for the coefficients due to the difficulty in choosing the tools, and the estimates are not statistically significant; hence, the two-stage GMM method is proposed by Araleno and Bond to solve this problem. Araleno and Bond proposed the following differential equation:

$$Y_{it} - Y_{it-1} = \alpha(Y_{it-1} - Y_{it-2}) + \beta(X_{it} - X_{it-1}) + (\varepsilon_{it} - \varepsilon_{it-1}) \tag{13}$$

That is, initially, differentiation is performed to remove the effects of sections or μ_i from the model and in the second stage, the residuals from the first stage are used to balance the variance-covariance matrix. In other words, this method creates variables called instrumental variables to have consistent estimates without bias (Baltagi, 2005). The consistency of the

GMM estimator depends on the validity of the assumption of error sentences and instruments' serial non-correlation, which can be tested by two tests specified by Araleno and Bond (1991), Araleno and Bower (1995), and Blundell and Bond (1998). The first one is the Sargan test of predetermined limits, testing the validity of the instruments. The Sargan test statistic (J-Statistic) has a distribution χ^2 with a degree of freedom equal to the number of excess restrictions. The second one is the serial correlation test, testing the presence of second-order serial correlation in the first-order differential error sentences using the M2 statistic. In this test, when there is no second-order serial correlation in the error statements from the first-order differential equation, the GMM estimator is consistent. Failure to reject the null hypothesis of both tests provides evidence for the hypothesis of no serial correlation and the validity of the instruments. In this study, Sargan's test was employed to check the consistency of the GMM estimator. Moreover, Eviews 13 and MATLAB software were used for statistical and econometric analysis, respectively.