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RESEARCH PAPER

Examining the Relationship between "Knowledge-Based Capital" and "Output per worker" in Iran's Manufacturing Sector

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Abstract
Researches show that knowledge-based capital (KBC) plays a significant role in modern economies, with this non-tangible type of capital being the greatest form of business investment and a major contributor to economic growth in advanced economies. Despite its importance as an important driver of economic growth, there are not enough researches that focus on the role of KBC in developing countries, so this paper aims to examine the relationship between KBC and Output per worker in Iran's manufacturing sector. To achieve this, we utilized a two-step estimation method; in the first step, we estimated KBC as a latent variable in the Iranian manufacturing sector using exploratory factor analysis. In the second step, we examined the relationship between KBC and Output per worker in Iran's manufacturing sector using a panel data regression analysis. Our findings indicate that KBC plays no significant role in Iran's manufacturing sector. A probable explanation of lower level of complexity in manufacturing sector of Iran is that the sector is not enough developed to need such factors to produce innovative and knowledge-based products, so, the knowledge-based capital has not a significant role in that. In another words, the manufacturing sector in Iran is yet equipment based and more relies on primary materials rather than high level knowledge-based factors.
Keywords: Exploratory Factor Analysis, Knowledge-Based Capital (KBC), Manufacturing Industries, Output.
JEL Classification: E22, O34.

1. Introduction
Recent economic literature is replete with words such as intangible capital, intellectual capital, knowledge-based capital (KBC), etc. In fact, these words have the same meaning and refer to a certain type of capital with two distinguishing

qualities (see for example, Ewens et al., 2025; OECD, 2013; Chahal and Bakhshi, 2016). As implied by the phrases intellectual and intangible, this type of capital is non- physical. Second, it is knowledge-based; therefore, KBC is a form of capital that is both intangible and unphysical and, as its name suggests, is based on knowledge that is gaining increasing relevance in modern, developed economies. In recent decades, KBC investment in developed economies has outpaced physical capital investment (machinery, equipment, and building). As seen in Figure 1, the aging population and natural resource restrictions in these countries have pushed them toward production enhancement methods and expanding economies, both of which are dependent on expanding innovations. These are referred regarded as endogenous growths in the growth literature, with investments in knowledge and innovation being the primary factors.

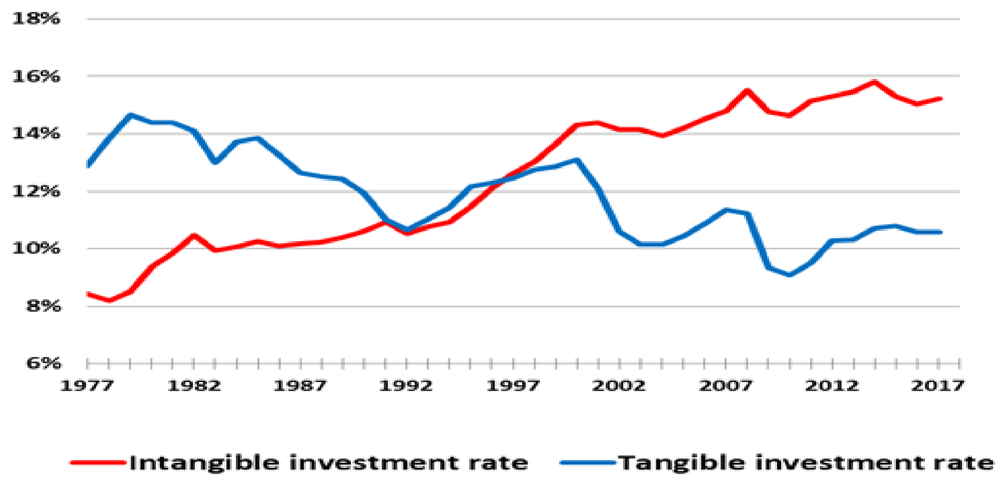

Figure 1. U.S. Investment, 1977 - 2017 (Nonresidential Business Investment Relative to Business Sector Gross Value Added)
Source: INTAN-Invest.

As stated previously, one of the primary characteristics of KBC is its intangibility, which makes its measurement problematic. In recent years, a great deal of research has been conducted to overcome this obstacle. In general, numerous scholars examine the subject of quantifying KBC at the country, industry and firm levels (Corrado et al., 2005), the pioneering study on the measurement of KBC, contributes to the solution by providing a stable framework for measuring KBC at the country level. Unlike efforts to assess KBC in developed countries, nothing is done in developing countries such as Iran. In the majority of developing countries, there is no definition of KBC in national accounts, making data collection nearly impossible.

Even though a great deal of study has been conducted at the micro level, it would be nearly impossible for a researcher to investigate KBC at this level due to data collection difficulties. Examining corporate balance sheets is a crucial aspect in measuring KBC at the firm level, as demonstrated by Ewens et al. (2025), who use the corporate incorporation method, based on balance sheet information, to estimate intangible capital at market prices. See also Marrocu et al. (2011), in which the authors evaluate the effect of intangible capital on firm-level productivity in six European countries using balance sheet data of firms for the period 2002 to 2006 and capitalizing intangible assets as intangible capital.

In developing countries such as Iran, however, we do not have access to reliable balance sheet information that may be utilized for KBC estimate. Furthermore, when it comes to intangible assets, Iran has poor accounting standards. Due to difficulties in collecting data at both the micro and macro levels in Iran, we examine KBC at the industry level in this work.

Moreover, the most influential, fundamental, and prominent works KBC have focused on developed countries while a few, do this for developing economies. This might have roots in weak databases in developing countries. In this research, we are going to study KBC in Iran as a developing country to fill the existing gap.

This paper investigates the relationship between KBC and Output per worker in Iran’s manufacturing. As there is no information about KBC regardless of the level of analysis, we must first estimate KBC in the manufacturing sector before examining its relationship with Output per worker. Consequently, this is a two-step estimation process in which we will first estimate KBC in manufacturing using exploratory factor analysis. In the second step of estimation, we use the estimated KBC as an explanatory variable to investigate the link between KBC and per capita production using a fixed-effect cross-section weighted panel data regression technique.

2. Knowledge-based Capital (KBC)

The last decades have witnessed dramatic growth in the economic (and social) importance of knowledge and learning (OECD, 2013; Stiglitz and Greenwald, 2014; Thelen, 2019). Knowledge-based or intangible capital like skills, patents, know-how, software or databases have become essential for surviving and thriving in today's economies (Haskel and Westlake, 2017).

KBC is a collection of assets that provide future benefits for firms. In contrast to machines, equipment, vehicles, and structures, however, these assets are not physical. This non-tangible form of capital is, increasingly, the largest form of business investment and a key contributor to growth in advanced economies (OECD, 2013).

According to a widely accepted classification, we can group KBC into three types:

- **Computerized information** (software and databases);
- **Innovative property** (patents, copyrights, designs, trademarks);
- **Economic competencies** (including brand equity, firm-specific human capital, networks of people and institutions, and organizational know-how that increases enterprise efficiency).

Table 1 sets out knowledge-based capital in three different classes.

Table 1. Classification of the Forms of KBC

Type of KBC asset	Type of knowledge-based capital
Computerized information	Knowledge embedded in, computer programs and computerized databases
Software	
Databases	
Innovative property	Knowledge acquired through scientific R&D and nonscientific inventive and creative activities
Research & Development	
Mineral explorations	
Copyright and creative assets	
New architectural and engineering designs	
Economic competencies	Knowledge embedded in firm-specific human and structural resources, including brand names
Brand-building advertisement	
Market research	
Worker training	
Management consulting	
Own organizational investment	

Source: OECD (2013); Corrado et al. (2005).

Table 1 offers a widely accepted definition of KBC; however, one can choose other classifications depending on a particular case study. For example, Chahal and Bakshi (2016) categorized intellectual capital into human capital, structural capital, and relational capital. In another case (Ewens et al., 2025) split intangible assets into knowledge and organizational capital.

In addition, Romer (2012) defines learning-by-doing as a factor of knowledge accumulation in his book and says: “The central idea is that, as individuals produce goods, they inevitably think of ways of improving the production process. For example, Arrow (1962) cites the empirical regularity that after a new airplane design is introduced, the time required to build the frame of the marginal aircraft is inversely proportional to the cube root of the number of aircraft of that model that has already been produced; this improvement in productivity occurs without any evident innovations in the production process. Thus, the accumulation of knowledge occurs in part not as a result of deliberate efforts, but as a side effect of conventional economic activity. This type of knowledge accumulation is known as *learning-by-doing*”.

3. Literature Review

KBC measurement is a novel and complex issue that has recently appeared in the literature with Corrado et al. (2005) as one of the pioneer publications in the issue. Corado et al. (2005) measured KBC according to the USA growth accounting framework where they added a time dimension to Solow’s growth accounting framework and defined capital as any use of resources in a way that increases the future consumption at the expense of today’s consumption. Hence, they take expenditures on intangible assets including R&D, copyright, movies, databases, and improved organizational structures, brand equity, and so on as investment items. To measure KBC, they collected data on expenditures on intangible assets according to the USA national accounting definitions. The results indicate that while investment in intangibles in the business is equal to that on tangibles, a large portion of this type of investment is not reflected in the USA’s national accounts. The findings also show that including intangible investment in national accounts could raise the average growth rate of real product and labor productivity in the late 1990s. Corrado et al. (2009), in line with the former literature, incorporated intangible capitals in the standard growth resources model (which has been used by BLS) and found that this adaption meaningfully changes the growth pattern in the united states, so that the rate of labor production change increases quickly and capital deepening becomes the dominant force in the labor productivity growth.

Therefore, the role of multifactor productivity has decreased proportionally whereas labor share of income has noticeably increased in the recent half a century. Corado et al. (2017), following the preceding research, while reviewing the literature on measuring KBC, estimated it across the Europe union and the united states based on their own expanded model in his 2005 paper. They also provided a summary of recent empirical evidence about the role of intangible capital as a stimulus for the growth of sectors and industries for all Europe Union countries and the United States to come up with examples of intangible assets` data applications. Van Ark et al. (2009) studied measurement methods of intangible capital and its share in economic growth using a comparison of investment in intangibles internationally and the degree to which this investment is embedded in 11 developed countries. They found that intangible assets have a comparatively large impact on economic growth in a way that, according to the study, they roughly account for one-fourth of productivity growth in the United States and big countries of Europe.

However, research on KBC is not limited to the macro level and there are several studies on the micro level. For example, Chahal and Bakshi (2016) measured KBC in the banking system of India as a developing country to stress the importance of KBC. They distributed questionnaires in 144 branches of 21 commercial private and public banks where due to the high level of experience and knowledge among the branch managers. The questionnaires were given to 3 executives and one senior manager of each branch. They used the confirmatory factor analysis method and also took human capital, relational capital, and structural capital as three dimensions of KBC. The results confirm that the whole dimensions of KBC have significant effects on it though relational capital has the most impact comparatively and human capital stands next to it.

Besides KBC measurement, much research has been done on the impact of KBC on economic growth and productivity at the macro, micro, industry, and firm level. At the macroeconomic level, Phale et al. (2021) examined the effects of pillars of a knowledge-based economy on economic growth in South Africa from 1998 to 2018 using a Cobb-Douglas production function and World Bank knowledge-based economy framework. Using a multivariate panel data model, they estimated both dynamic and static long-rum relations which show government effectiveness, saving adjusted on education expenditures, tertiary enrollment, technical and scientific journals, and mobile cellular subscriptions positively impact economic growth. The findings indicate that the innovation pillar is the most influential element that affects economic growth and next to it are education, skill, and information and communication infrastructures. In addition, Abdih et al. (2006) empirically investigated the knowledge production function by looking for cointegration relations. They found two long-run cointegration relations where the first depicts long-run production function and the second points to a long-term, positive relationship between total factor productivity and knowledge stock.

Following the importance of intangible investment on productivity growth in developed economies, Corrado et al. (2014) set out intangibles investment data by industry for 14 EU countries in 1995-2010 and industry growth accounting incorporating these data for 8 countries. The results show that though intangible investment has increased in the service and manufacturing sectors, the increase has been more intense in the service. According to the other findings, intangible assets have the same share in labor productivity growth in both sectors, service, and manufacturing, and in developed countries, this share exceeds the effect of improved labor quality. Corrado et al. (2014) also showed that, in countries with high economic growth, those with good performance in both manufacturing and service have in general experienced higher productivity growth. Finally, they observed that countries with very low TFP (which stands for total factor productivity) growth have low labor productivity growth. One of the papers examining intangible assets' impact on productivity growth is Crass, Peters (2014). They simultaneously compare the effects of innovative capital, human capital, branding capital, and organizational capital on productivity and looked for complementarity or substitutability between these types of capital. The results indicate that human capital and branding capital have a noticeable, positive impact on productivity whereas licenses and patents have a slight influence on raising productivity; likewise, the same is true for organizational capital. The authors also found several complementarities between different kinds of intangible assets. Another study by Siedschilage (2019) looks into the representativeness of firm productivity to investment in knowledge-based capital including a range of intangible assets such as R&D, intellectual property assets, computer software, organizational, and branding capital in Ireland, a small open economy. This study gets rid of the representative firm assumption and takes into account the heterogeneous behavior of firms that differ with respect to size, export participation, and type of sector they are active in. Based on the findings, simultaneous investment in any type of KBC, has complementary and substitutionary effects on a firm`s productivity and these patterns of correlation are different among different kinds of firms and sectors.

Felix (2019) reviewed the literature on the effect of investment in intangible assets on labor productivity growth at the country, industry, and firm levels. They concluded that investment in intangible assets has gained increasing importance in explaining the dynamics of labor productivity.

To end our discussion in this section, we look into mechanisms through which KBC impacts economic growth. There exists much research on this topic, especially OECD (2013), a comprehensive study that focused on the relationship between KBC, reallocation, and productivity growth. The report vividly shows that how providing basis and factors (competition, trade specialization, institutional capacities, production factors stock, and knowledge infrastructure) affects investment in KBC and leads to productivity growth in an economy. According to this report, firms` investment in KBC would result in efficient allocation and productivity growth. With respect to technology, firms are either on the frontiers of technology or far from it, hence competition pressures would end up in the continuation of firms' innovative activities keeping them on the boundaries of technology. Aghion and Howitt (1992) believe that when exposed to competitive pressures, firms continue their innovative activities to stay on the frontiers of expanding new and innovative technologies. On the other hand, for firms far from the frontiers, investing in KBC is crucial since those who have done a poor job in this area might be forced to descale or exit the market which in turn frees up resources for the firms producing with the most efficient technologies. Eventually, through this mechanism, firms with the highest productivity would gain the largest market shares; a fact that ends in efficient resource allocation (Olley and Pakes, 1996). Riley and Robinson (2011) examined the relationship between intangible assets and economic growth from different angles and illustrate that intangible assets affect, both directly and indirectly, the production process through innovation. According to this study, taking intangible assets as a production factor first enhances productivity at the firm level and then, by improving firms` performance due to incorporating intangible assets into the production process, increases the economy`s performance at both sectoral and regional levels which finally results in a raise in productivity in national accounts and economic growth.

Note that Research on the KBC is not restricted to the areas described above. For example, Seidl (2023) concentrated on the role of public investments and the organization of societies on the formation of KBC. He found that corporatist countries invest a lot more in knowledge-based capital, and corporatism also affects how countries react to deindustrialization. This is an important finding given the key role of long-term policy making in areas like climate change politics, pandemic preparedness or responding to the digital transformation. Also, Lasinio et al. (2019) investigated the role of knowledge-based capital for participation and value appropriation in global value chains (GVC) for a sample of European countries over 1995–2011. They find that knowledge-based capital is positively correlated with participation and value appropriation along the value chain.

4. Model Specification

Our empirical model is based on the production function of the firm, as technical possibility of the firm. According to the literature, we conjecture that, KBC as a form of capital will affect firms' technology from the production function channel. To analyze the role of KBC in the industry, our approach is to investigate its role in industrial production function as a factor. So, following Di Ubaldo and Siedschlag (2021) as well as Crass and Peters (2014), the Cobb-Douglas production function is as follows:

$$Q_{it} = A_{it}\, L_{it}{}^{\alpha_l} M_{it}{}^{\alpha_m}\, C_{it}{}^{\alpha_c}\, K_{it}{}^{\alpha_k}\, e^{\varepsilon_{it}} \tag{1}$$

Q_{it}: is output (real value added) in industry *i* at time *t*;
A_{it}: are exogenous factors (other than factors of production) that affect output in industry *i* at time *t*;
L_{it}: is number of labors in industry *i* at time *t*;
M_{it}: is raw material in industry *i* at time *t*;
C_{it}: is physical capital accumulated in industry *i* at time *t*;
K_{it}: is KBC accumulated in industry *i* at time *t*;
e_{it}: is stochastic shock to output in industry i at time *t*;
α_l, α_m, α_c and α_k: the output elasticities of inputs.

To model we assume that A_{it} can be decomposed as follow:

$$A_{it} = \theta_i \mathrm{u}_t \tag{2}$$

where u_t is exogenous factors that affect production function at levels above the industry, such as macroeconomic conditions (invariant to *i* but variable at the time dimension t), and θ_i and industry-specific factors other than inputs.

Put A_{it} in Equation 1 and take the logarithm to obtain the following equation:

$$q_{it} = \theta_i + u_t + \alpha_l l_{it} + \alpha_m m_{it} + \alpha_c c_{it} + \alpha_k k_{it} + \varepsilon_{\boldsymbol{it}} \tag{3}$$

Within which small letters denote the respective log values of output and inputs in industry *i* at time *t*, ε_{it} is the error term which accounts for unobserved shocks and measurement errors.

Output per worker is obtained from equation 3 as follows:

$$q_{it} - l_{it} = \theta_i + u_t + (\alpha_l - 1)\, l_{it} + \alpha_m m_{it} + \alpha_c c_{it} + \alpha_k k_{it} + \varepsilon_{\boldsymbol{it}} \tag{4}$$

Equation 4 can be further written as follows:

$$q_{it} - l_{it} = \theta_i + u_t + (\alpha_l + \alpha_m + \alpha_c + \alpha_k - 1)l_{it} + \alpha_m(m_{it} - l_{it}) + \alpha_c(c_{it} - l_{it}) + \alpha_k(k_{it} - l_{it}) + \varepsilon_{it} \quad (5)$$

Assuming constant returns to scale assumption, $\alpha_l + \alpha_m + \alpha_k + \alpha_c = 1$, Equation 4 becomes:

$$q_{it} - l_{it} = \theta_i + u_t + \alpha_m(m_{it} - l_{it}) + \alpha_c(c_{it} - l_{it}) + \alpha_k(k_{it} - l_{it}) + \varepsilon_{it} \quad (6)$$

$q_{it}-l_{it}$: Output per worker of industry *i* at time *t*,
$m_{it} - l_{it}$: material per worker in industry *i* at time *t*.
$c_{it} - l_{it}$: physical capital per worker in industry *i* at time *t*;
$k_{it} - l_{it}$: knowledge-based capital per worker in industry *i* at time *t;*

To complete Equation 6, u_t, and θ_i must be specified. For u_t, we can employ variables GDP growth and economic openness as macro-level exogenous industry-determining factors denoted by GDP and Openness[1], respectively. θ_i, represents industry-specific variables that do not change over time but differ by industry. The empirical regression equation can be expressed as follows:

$$q_{it} - l_{it} = \theta_i + \alpha_m(m_{it} - l_{it}) + \alpha_c(c_{it} - l_{it}) + \alpha_k(k_{it} - l_{it}) + \alpha_1 openness + \alpha_2 Gdp + \varepsilon_{it} \quad (7)$$

5. Empirical Strategy

5.1 Dataset

Our econometric framework has a two-stage structure in which we estimate KBC in the first stage and use this estimation as a variable in the second. In the majority of developing countries, including Iran, there is no complete and reliable database about science and technology, but we can estimate knowledge-based capital using other databases. The Iranian statistical center publishes a comprehensive database for Iranian manufacturing firms which covers International Standard of Industrial Classification (ISIC) codes up to 4-digit, covering firms that have 10 and more employees. Due to changes in ISIC version over time, 4-digit codes have deficiencies, including changes in code definitions; so, we choose to use 2-digit ISIC codes (containing ISIC codes 10 to 33) to estimate our regression equation and the KBC for each 2-digit manufacturing code. Our dataset covers the years 2002 to 2018. In the second stage, following the estimation of KBC, we evaluate the influence of KBC on Output per worker at the industrial level. To accomplish this, we specify the production function with precision and estimate the final model. We chose the manufacturing sector because, unlike other sectors, not only

[1]. See for example, Wong (2009); Umoh and Effiong (2013).

is there sufficient information available, but it also contains the necessary level of detail for this analysis.

5.2 Estimation of KBC

To estimate KBC, we have adopted the exploratory factor analysis (EFA) method. As to why we took EFA approach, it suffices to say that KBC is intangible so we can treat it as a latent factor in the factor analysis method. EFA method aims to discover some details about the nature of independent variables influencing the dependent variable, which is unobservable directly but can be traced out by observable variables. The main idea in the exploratory factor analysis is that, although KBC is not observable directly, its footprint can be traced out in variables correlated with it. There exist similar papers using factor analysis to measure KBC, for example, Chahal and Bakshi (2016) estimated KBC in India`s banking sector using the confirmatory factor analysis method.

In the exploratory factor analysis, it is necessary to choose variables that are related to KBC, such that every variable denotes one aspect of the latent variable, KBC. It is like painting an object, by looking at its shadow. In the factor analysis, the linkage between the latent variable, the KBC, and observable variables is constructed by "factor loadings". Factor loadings should be estimated by an appropriate method, here we have used the Maximum Likelihood method, to estimate the factor loadings. After choosing variables and estimating the factor loadings for every observable variable in the first stage, we can compute the estimated KBC.

The factor analysis regression used in the first stage is comprised of two types of variables, dependent and independent (latent) variables where the last one is called the factor. Table (2) indicates independent variables in the factor analysis model. According to the literature, we can divide the variables into 5 major groups including learning-by-doing[1], computer knowledge, innovative asset, economic competence, and human capital. In fact, we conjecture that variables in each group would explain one aspect of the latent knowledge-based capital, including the groups classified in Table 2.

[1]. Inclusion of simple workers and workers with low levels of education is because of two different purposes. First, through learning by doing channel, as noted by arrow (1962) and emphasized by Romer (2012), knowledge accumulation is not necessarily through purposeful efforts, but it can be caused by repetition of a simple work in the production process, done even by simple workers. Second, our purpose to inclusion of that variables is also to estimate and compare the roles of deferent levels of education on the KBC accumulation.

Table 2. Exploratory Factor Analysis of the Dependent Variables for KBC Estimation by 2-Digite ISIC Codes

Group	Row	Variable symbol	Definition
Learning-by-doing	1	WSIMPLE	Share of simple workers in total workers in the production lines
	2	WSKILLED	Share of skilled workers in total workers in the production lines
Computer knowledge	3	SSOFTWARE	Ratio of expenditures on computer software to the sale
Innovative asset	4	SRESEARCH	Ratio of expenditures on R&D to the sale
Economic competence	5	SEXPORT	Ratio of exports to the sale
	6	SEDUC	Ratio of expenditures on training to the sale
	7	SCOMISION	Ratio of expenditures on sale commission to the sale
	8	SADVERTISING	Ratio of expenditures on advertising, banners and press to the sale
Human capital	9	WTECH	Share of technicians in total workers in the production lines
	10	WENG	Share of engineers in total workers in the production lines
	11	PHDRATIO	Share of workers with PhD grade in total literate employees
	12	MASTERRATIO	Share of workers with Master's degree in total literate employees
	13	LICANSERATIO	Share of workers with bachelor degree in total literate employees
	14	COLLEGERATIO	Share of workers with college degree in total literate employees
	15	DIPLOMARATIO	Share of workers with diploma degree in total literate employees
	16	SCHOOLRATIO	Share of workers with workers less than diploma degree in total literate employees

Source: Research finding.

5.3 The Estimation of Labor Productivity Equation

After the estimation of KBC using the factor analysis, we can estimate Equation (7) to analyze effects of KBC on Output per worker in the manufacturing sector of the Iranian economy. To do that, it is necessary to quantify the variables in Equation (7). Based on the Iranian Statistical Center's database of manufacturing firms, we have the following data for the variables of the Equation (7):

VA_{it}= Real[1] value added in industry *i* at time *t*;

L_{it} =Number of employees in industry *i* at time *t*;

M_{it}= value of raw materials consumed in industry *i* at time *t*;

$Equipment_{it}$= as a proxy for C_{it}, fixed capital investment in industry *i* at time *t*; which is included investments in equipment, computer software and hardware. In other words, we included any fixed investment other than land and buildings in every ISIC code;

L_{it}= Total number of employees in each ISIC code in every year;

KBC_{it}= Knowledge-Based Capital in industry *i* at time *t* (estimated by factor analysis);

GDP_t=Real GDP growth of the Economy[2] at time *t*;

$Openness_t$= the index of economic openness at time *t*;

The openness is measured in macro-level as follow: $openness = \frac{Export+Import}{Gdp}$ where *Export* and *Import* are respectively value of non-oil export and total import of the Iran economy.

Ultimately, we have θ_i, the industry-specific effect, which may be fixed or random; we will select between the two based on the Hausman test for fixed or random effects.

6. Empirical Result

According to Table (3), as to factor analysis model, we estimated one factor which we can take as KBC; in other words, there is a latent factor which its influence on dependent variables is observable. As it is obvious in Table (3), the Bartlett chi-square is significant at 5 percent type I error, rejecting the null hypothesis that the correlation matrix of the variables is diagonal. In other words, the hypothesis that there are no correlation and covariance between variables of interest is rejected at 5 percent level, indicating that there is a significant relationship between the variables, and we can think that, the KBC is the linkage between the variables.

[1]. Data for value added in each ISIC code are expressed in nominal values (Iranian Rial). To convert them to real values, we used the deflator index used by the Iranian Statistical Centre to deflate each ISIC codes. This is also true for other nominal data that we used in Equation 7.

[2]. The macro data such as GDP and export and import values are obtained from Iranian Central Bank Database.

Table 3. Results of the Factor Analysis (First Estimation)

	Loadings F1	Communality	Uniqueness
WTECH	0.606890	0.368315	0.631685
WSKILLED	-0.550891	0.303481	0.696519
WSIMPLE	-0.457630	0.209426	0.790574
WENG	0.901950	0.813514	0.186486
SSOFTWARE	0.006302	3.97E-05	0.999960
SRESEARCH	0.291097	0.084737	0.915263
SEXPORT	0.001954	3.82E-06	0.999996
SEDUC	0.270344	0.073086	0.926914
SCOMISION	0.185389	0.034369	0.965631
SCHOOLRATIO	-0.828722	0.686780	0.313220
SADVERTISING	0.088443	0.007822	0.992178
PHDRATIO	0.275550	0.075928	0.924072
MASTERRATIO	0.838383	0.702886	0.297114
LICENSERATIO	0.978772	0.957995	0.042005
DIPLOMARATIO	0.016236	0.000264	0.999736
COLLEGERATIO	0.735612	0.541125	0.458875

Factor method: Maximum likelihood

Number of factors: Minimum average partial

Source: Research finding.

Table 4. Model Analysis

Chi-square statistic	12916.93
Chi-square prob.	0.0000
Bartlett chi-square	12700.06
Bartlett probability	0.0000
Parameters	32
Degree-of-freedom	104

Source: Research finding.

The results in Table 3 show that all the variables but simple workers, skilled workers, and literate workers without a diploma have a positive and direct correlation with KBC[1]. Looking at wskilled and wsimple factor loadings indicates that the more investment in KBC by the firms, the less will be important to the learning-by-doing in a firm and the more will be the role of academic education for the firms. This notion makes a positive relation between KBC and the level of academic education of workers of the firms. As it is obvious when looking at the

[1]. In the factor analysis approach, variables having a higher correlation with a factor, which is measured by the factor loading, fall into that factor's group. The larger the factor loadings, the greater influence of the variable in explaining the factor.

coefficients of variables capturing workers` education (variables 11 to 16 in Table2), the conclusion will be confirmed.

SSOFTWARE coefficient indicates that investment in computer software has a small though positive impact in developing KBC in the Iranian manufacturing sector. In other words, KBC in the sector has not yet had enough embodiments in the form of software knowledge. Besides, export and advertising have the lowest coefficients in the economic competence group. Overall, it can be said that KBC (the latent factor in question) is mostly influenced by the education level of the labor force.

Table 4 displays the results of the second step estimation, estimation Equation7, in terms of the 2-digit ISIC codes of Iranian manufacturing firms. Before executing Equation 7, we conducted two specification tests: the Redundant Fixed Effects Test (see Appendix) and the Correlated Random Effects-Hausman Test. These tests were used to determine the nature of the θ_i in Equation 7. As described above, θ_i is unobserved heterogeneity within each ISIC code (the industry-specific effects). First, it is crucial to determine whether or not there are significant industry-specific differences between the data. To do this, we conducted Redundant Fixed Effects using the F-statistics and the chi-squared statistics to examine the hypothesis that there is no significant industry-specific heterogeneity in the data. The null hypothesis cannot be accepted based on the statistics and 5% type I error; therefore, we must specify θ_i as industry-specific heterogeneity. Then, using the Hausman Test, it must be established whether the effects are random or fixed. To perform the Hausman test, we must model random effects using generalized least squares and estimate Equation 7. The estimation results (given in the appendix) show that all variances of the random part of the equation are due to the idiosyncratic stochastic part and the individual effects have zero variances. This shows that the random effects are not appropriate for estimation of the equation. Because of the zero variances of the random effects, the standard errors of the Hausman test are not consistent with the assumptions of the test (see the results of the Hausman test in the appendix) and then, the results of the test are not reliable. The crucial assumption of random effects estimates is that there is not any correlation between θ_i and the explanatory variables, which is also the null hypothesis of the Hausman test. Since the Hausman test's assumptions and random effects are unreliable, it is preferable to utilize the fixed effects estimating approach, which is robust to the correlation between individual effects ($\theta_i s$) and explanatory variables of the Equation 7. Therefore, the robustness of the fixed effects model in the presence of a probable correlation between θ_i,s and the explanatory variables leads us to select it.

Based on the results of the specification tests, we should specify θ_i,s as fixed effects. Table 5 displays the results of the fixed effects estimation of Equation 7. As is clear, the adjusted R-squared is approximately 96%, showing that the explanatory variables in Equation 7 are capable of explaining 96 percent of the variations of the Output per worker in terms of 2-digit ISIC codes of the Iranian manufacturing sector. Because of possible autocorrelation problem in the regression residuals, we have adjusted the standard errors to be robust against autocorrelation. As there are no lagged dependent variables on the right side of Equation 7, the Durbin-Watson test is valid. Also, for robust standard errors in the case of probable heteroscedasticity, we selected White diagonal standard errors & covariance for the parameter standard errors.

Table 5. Estimation Results of Equation 7, the Dependent Variable Is the Logarithm of the Value Added per Worker in ISIC Codes

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	-4.767829	0.300958	-15.84220	0.0000
LOG(EQUIPMENT/L)	0.070618	0.017546	4.024674	0.0005
LOG(M/L)	0.652133	0.050526	12.90701	0.0000
LOG(KBC/L)	0.038121	0.025765	1.479568	0.1526
LOG(OPENNESS)	0.092503	0.044337	2.086340	0.0482
GDP	0.003160	0.001225	2.580324	0.0167
Effects Specification				
Cross-section fixed (dummy variables)				
Weighted Statistics				
Root MSE	0.223568	R-squared		0.963148
Mean dependent var	-1.512925	Adjusted R-squared		0.960425
S.D. dependent var	1.481071	S.E. of regression		0.231963
Sum squared resid	20.39287	F-statistic		353.7626
Durbin-Watson stat	0.929103	Prob(F-statistic)		0.000000
Unweighted Statistics				
R-squared	0.906278	Mean dependent var		-0.624076
Sum squared resid	26.46975	Durbin-Watson stat		0.418829

Source: Research finding.

As demonstrated, all explanatory variables, except KBC are significant at a type I error level of 5% and each has a positive effect on output per worker. For our purposes, it is obvious that the coefficient of KBC is not significant even at

10% type I error, although it has a positive sign. The economic openness coefficient is significant and positive indicating that the more open an economy is to the world economy, the greater the labor productivity gains for Iran's manufacturing firms.

Comparing coefficient values, it is obvious that material has greatest positive impact on output per worker in each Iranian manufacturing codes, which shows that among other things, the output in Iranian manufacturing sector is dependent more on the availability of materials. Equipment has also positive and significant coefficient which shows that in Iran's manufacturing sector, physical capital has a significant and important role in production processes. The coefficient of KBC is not significant, which we can interpret it as follow. Because manufacturing sector in Iran is not enough knowledge based, so its demand for knowledge-based capital is also insignificant. Principally, knowledge-based capital is of such intangible assets that applicable in high level processes of productions. For example, activities of research and development, data gathering and analysis and so on. According to our dataset, average ratio of research costs to total sales was 0.083 percent, which is less than 0.1 of 1 percent. As another example, in our dataset, average ratio of expenditures in computer software to total sales was 0.031 of percent. The figures show that investment in intangible knowledge-based items in manufacturing sector of Iran is very low. Our interpretation is that the sector is not enough developed to need such factors to produce innovative and knowledge-based products. In another words, the manufacturing sector in Iran is yet equipment based and more relies on primary materials rather than high level knowledge-based factors.

The significant coefficient of economic openness shows that economic policies in the form of a more closed economy and greater limitations on foreign commerce will have a negative impact on labor productivity in the Iranian manufacturing sector. Another aspect of this coefficient is that, in a more open economy there is more facilitate to provide material and equipment that should be imported.

Finally, GDP has also a positive significant coefficient which can be interpreted as positive impacts of better macroeconomic conditions on economic performance of manufacturing industry in Iran.

7. Conclusion

KBC plays a significant role in modern economies, with this non-tangible type of capital being the greatest form of business investment and a major contributor to economic growth in advanced economies. Despite its importance as an important driver of economic growth, there are not enough researches that focus on the role of KBC in developing countries, so the aim of this paper was to examine the relation between KBC with Output per worker in Iran`s manufacturing sector. To do that, we have adopted a two-step estimation method; in the first step using the exploratory factor analysis method, we have estimated KBC, as a latent variable, in the Iranian manufacturing sector.

In the second step, we have estimated a per worker production function to analyze the effects of factors of production in Iranian manufacturing industry. Our results show that material has greatest positive impact on output per worker in each Iranian manufacturing codes, which show that among other things, the output in Iranian manufacturing sector is dependent more on the availability of materials. Equipment has also positive and significant coefficient which show that in manufacturing sector in Iran physical capital has a significant and important role in production processes.

The coefficient of KBC is not significant at 5 percent type I error, which we can interpret it as follow. Because manufacturing sector in Iran is not enough knowledge based, so its demand for knowledge-based capital is also insignificant. Principally, knowledge-based capital is of such intangible assets that applicable in high level processes of productions. Our interpretation is that the sector is not enough developed to need such factors to produce innovative and knowledge-based products. In another words, the manufacturing sector in Iran is yet equipment based and more relies on primary materials rather than high level knowledge-based factors.

The results show that economic policies in the form of a more closed economy and greater limitations on foreign commerce will have a negative impact on labor productivity in the Iranian manufacturing sector. Another aspect of this coefficient is that, in a more open economy there is more facilitate to provide material and equipment that should be imported. And finally, our results show that there is a positive relationship between better macroeconomic conditions and Output per worker of the manufacturing industry in Iran.

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Appendix

Eviews Outputs

1. Redundant Fixed Effects Tests

Redundant Fixed Effects Tests
Equation: EQ1
Test cross-section fixed effects

Effects Test	Statistic	d.f.	Prob.
Cross-section F	101.643371	(23,379)	0.0000
Cross-section Chi-square	803.626538	23	0.0000

Cross-section fixed effects test equation:
Dependent Variable: LOG(Q/L)
Method: Panel Least Squares
Date: 12/09/22 Time: 18:44
Sample: 1381 1397
Periods included: 17
Cross-sections included: 24
Total panel (balanced) observations: 408
White period (cross-section cluster) standard errors & covariance (d.f. corrected)
Standard error and t-statistic probabilities adjusted for clustering

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-2.573766	0.971450	-2.649405	0.0143
LOG(EQUIPMENT/L)	0.086614	0.082258	1.052961	0.3033
LOG(M/L)	0.425559	0.055671	7.644230	0.0000
LOG(KBC/L)	0.137982	0.083521	1.652060	0.1121
LOG(OPENNESS)	0.131650	0.138224	0.952438	0.3508
GDP	0.009496	0.004884	1.944239	0.0642

Root MSE	0.659622	R-squared	0.371445
Mean dependent var	-0.624076	Adjusted R-squared	0.363628
S.D. dependent var	0.833022	S.E. of regression	0.664527
Akaike info criterion	2.035113	Sum squared resid	177.5214
Schwarz criterion	2.094102	Log likelihood	-409.1630
Hannan-Quinn criter.	2.058455	F-statistic	47.51252
Durbin-Watson stat	0.061471	Prob(F-statistic)	0.000000

2. Random Effects Estimation

Dependent Variable: LOG(Q/L)
Method: Panel EGLS (Cross-section random effects)
Date: 12/09/22 Time: 18:47
Sample: 1381 1397
Periods included: 17
Cross-sections included: 24
Total panel (balanced) observations: 408
Swamy and Arora estimator of component variances
White period (cross-section cluster) standard errors & covariance (d.f. corrected)
Standard error and t-statistic probabilities adjusted for clustering

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-3.697202	0.897371	-4.120037	0.0004
LOG(EQUIPMENT/L)	0.116856	0.089270	1.309015	0.2035
LOG(M/L)	0.513351	0.123640	4.151965	0.0004
LOG(KBC/L)	0.105177	0.061665	1.705616	0.1016
LOG(OPENNESS)	0.184192	0.113811	1.618397	0.1192
GDP	0.009421	0.004037	2.333540	0.0287

Effects Specification

	S.D.	Rho
Cross-section random	0.659676	0.8694
Idiosyncratic random	0.255621	0.1306

Weighted Statistics

Root MSE	0.253264	R-squared	0.537072
Mean dependent var	-0.058394	Adjusted R-squared	0.531314
S.D. dependent var	0.372691	S.E. of regression	0.255147
Sum squared resid	26.17017	F-statistic	93.27695
Durbin-Watson stat	0.489962	Prob(F-statistic)	0.000000

Unweighted Statistics

R-squared	0.346285	Mean dependent var	-0.624076
Sum squared resid	184.6273	Durbin-Watson stat	0.069450

3. Hausman Test

Correlated Random Effects - Hausman Test
Equation: EQ1
Test cross-section random effects

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.

Cross-section random	0.000000	5	1.0000

* Cross-section test variance is invalid. Hausman statistic set to zero.
** WARNING: robust standard errors may not be consistent with assumptions of Hausman test variance calculation.

Cross-section random effects test comparisons:

Variable	Fixed	Random	Var(Diff.)	Prob.
LOG(EQUIPMENT/L)	0.116616	0.116856	0.000665	0.9926
LOG(M/L)	0.520431	0.513351	0.003225	0.9008
LOG(KBC/L)	0.096407	0.105177	0.001332	0.8101
LOG(OPENNESS)	0.187252	0.184192	0.000500	0.8912
GDP	0.009328	0.009421	0.000001	0.9368

Cross-section random effects test equation:
Dependent Variable: LOG(Q/L)
Method: Panel Least Squares
Date: 12/09/22 Time: 18:47
Sample: 1381 1397
Periods included: 17
Cross-sections included: 24
Total panel (balanced) observations: 408
White period (cross-section cluster) standard errors & covariance (d.f. corrected)
Standard error and t-statistic probabilities adjusted for clustering

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-3.836455	1.066619	-3.596836	0.0015
LOG(EQUIPMENT/L)	0.116616	0.092919	1.255028	0.2221
LOG(M/L)	0.520431	0.136060	3.825012	0.0009
LOG(KBC/L)	0.096407	0.071655	1.345443	0.1916
LOG(OPENNESS)	0.187252	0.115988	1.614412	0.1201
GDP	0.009328	0.004204	2.218952	0.0366

Effects Specification

Cross-section fixed (dummy variables)

Root MSE	0.246369	R-squared	0.912315
Mean dependent var	-0.624076	Adjusted R-squared	0.905837
S.D. dependent var	0.833022	S.E. of regression	0.255621
Akaike info criterion	0.178185	Sum squared resid	24.76468
Schwarz criterion	0.463300	Log likelihood	-7.349752
Hannan-Quinn criter.	0.291006	F-statistic	140.8319
Durbin-Watson stat	0.518534	Prob(F-statistic)	0.000000

4. Results of Equation 7:

Dependent Variable: LOG(Q/L)
Method: Panel EGLS (Cross-section weights)
Date: 12/09/22 Time: 18:48
Sample: 1381 1397
Periods included: 17
Cross-sections included: 24
Total panel (balanced) observations: 408
Linear estimation after one-step weighting matrix
White period (cross-section cluster) standard errors & covariance (d.f. corrected)
Standard error and t-statistic probabilities adjusted for clustering

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-4.767829	0.300958	-15.84220	0.0000
LOG(EQUIPMENT/L)	0.070618	0.017546	4.024674	0.0005
LOG(M/L)	0.652133	0.050526	12.90701	0.0000
LOG(KBC/L)	0.038121	0.025765	1.479568	0.1526
LOG(OPENNESS)	0.092503	0.044337	2.086340	0.0482
GDP	0.003160	0.001225	2.580324	0.0167

Effects Specification

Cross-section fixed (dummy variables)

Weighted Statistics

Root MSE	0.223568	R-squared	0.963148
Mean dependent var	-1.512925	Adjusted R-squared	0.960425
S.D. dependent var	1.481071	S.E. of regression	0.231963
Sum squared resid	20.39287	F-statistic	353.7626
Durbin-Watson stat	0.929103	Prob(F-statistic)	0.000000

Unweighted Statistics

R-squared	0.906278	Mean dependent var	-0.624076
Sum squared resid	26.46975	Durbin-Watson stat	0.418829

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