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ARTICLE

The effect of knowledge spillovers and human capital through technological intensity on employment growth in Indonesia

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Abstract

This study estimates the effects of externalities of agglomeration in the form of knowledge spillovers (Marshall–Arrow–Romer/job specialization, Jacobs/diversity, and Porter/competition) and of externalities obtained from human capital on employment growth based on the technological intensity in an industry. We employed the data of International Standard Industrial Classification of all Economic Activities two-digit numerical codes for manufacturing industries at the level of districts and cities in Indonesia in 2010 and 2015 and ran the estimation model using ordinary least squares. The results show that while employment growth is constrained by specialization, it is complied by diversity though it is statistically insignificant across technological intensity in the industry. Competition has negative effects on both low- and medium–low-technology industries; however, it has positive effects on high-technology industries. Additionally, human capital negatively affects low-technology industries, while it positively affects medium–low and high-technology industries.

Keywords Knowledge spillovers · Employment growth · Technology · Human capital · Indonesia

JEL classification O18 · O33 · R11

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1 Introduction

The manufacturing industry has been a major driver of Indonesia's economy contributing one-third of its GDP with an annual growth rate of 12% since 1991. However, these accomplishments declined when successive economic, financial, and political crises hit Indonesia during 1997–1998. After the crises, manufacturing sector's performance did not fully recover and was expected to be slower than in other countries (World Bank 2012). The revitalization of the sector is necessary considering the crucial role it plays in providing better jobs in terms of both quality and quantity.

However, despite its great potential, the data from Indonesia Statistics (2017) showed that employment growth in the manufacturing sector (2–5%) was far below the GDP growth (5–7%) and the output growth from manufacturing sector (5–20%)[1]. Therefore, it can be argued that improving job opportunities/labor absorption becomes paramount in the process of revitalizing the manufacturing sector, considering the size of Indonesia's population.

One of the factors affecting the growth of the manufacturing industry is the externalities generated from the agglomeration process in the form of knowledge spillovers, both within similar industries and between different industries. The well-known theories supporting such an argument are those proposed by Marshal–Arrow–Romer (MAR), Jacobs, and Porter. MAR's theory of job specialization emphasizes the role of knowledge spillovers generated within similar industries (specialization) and of local monopoly. This theory accords with Porter's theory of competition; however, it highlights s the importance of competition to induce growth. Jacob's theory of diversity states that knowledge spillovers occurring between different industries (cross-sectional spillovers/diversity) direct growth (Glaeser et al. 1992). Further empirical l studies on the effects of knowledge spillovers on employment growth equally exhibits distinct findings regarding the externalities that regulate growth.

Previous research has established that while Jacobs' notion of externalities advocates employment growth, MAR's concept of specialization inhibits this matter (Glaeser et al. 1992; Deidda et al. 2003; Van Oort 2007). Henderson et al. (1995) confirmed that MAR's externalities have positive effects on employment growth in the traditional industrial sectors (mature industry). In the case of Indonesia, Khoirunurrofik (2018) discovered that, in general, whereas specialization results in the undesirable effects of the employment growth in the manufacturing industry diversity indicates favorable outcomes. A study by Ercole and O'Neill (2017) noted that diversity and competition have positive impacts on the employment growth, while the effects of specialization on this concern are statistically insignificant. The various findings of the previous studies are as a result of the different analyses of aggregation of sectors/industries/regions, measurement variables, and the foremost control variables employed in the model (Combes 2000; Van Oort 2007; De Groot et al. 2016). In addition, the influence of knowledge spillovers on the employment

[1] Employment, GDP, and output growth of the manufacturing sector compared to the previous year during 2011–2015.

growth differs based on technological intensity in the industry (Henderson et al. 1995; Heidenreich 2009; Hartog et al. 2012; Khoirunurrofik 2018; Liang and Goetz 2018). These studies discovered that whereas diversity is an advantage to high-technology industries, specialized regions are advantageous to low-technology industries.

However, none of the abovementioned studies has investigated the influence of another form of knowledge spillover—technological intensity-based competition. Additionally, up to now, far too little attention has been paid to the effects of human capital as the vehicle or source of knowledge spillovers based on technological intensity. This study contributes to our understanding of the effects of knowledge spillovers from specialization, diversity, and competition, along with human capital, across different technological intensities. Specifically, this study estimates the effects of externalities obtained from agglomeration (MAR/specialization, Jacobs/diversity, and Porter/competition) in conjunction with human capital on employment growth based on the technological intensity in the industry.

The rest of the paper is structured as follows. A literature review on the relationship between technological intensity and knowledge spillovers is presented in the discussion that follows. The next section presents research methods including data, variables, and the empirical strategy employed, followed by results and analyses. The final section presents conclusion and recommendations.

2 Literature review

Marshall's theory of job specialization identifies three mechanisms that generate benefits/positive externalities in agglomeration: knowledge spillovers, labor market pooling, and input sharing, which can be observed in a temporal scope (Rosenthal and Strange 2004). The interaction between one economic agent and others in the past affects productivity in the present. In other words, static agglomeration economics highly likely generates dynamic agglomeration economics (Rosenthal and Strange 2004).

Static externalities are associated with cost efficiency and industrial location. Meanwhile, dynamic externalities relate more to knowledge and technological spillovers affecting growth. The debate on dynamic externalities has focused on two primary theories: MAR's theory of job specialization and Jacob's theory of diversity, and was later extended by Porter's competition theory (Glaeser et al. 1992). MAR's theory focuses on how spillovers are revitalized among firms within the same sectors/industries. According to this theory, technological/knowledge spillovers are one of the benefits of industrial agglomeration or industrial localization. Marshall further explained that the latter becomes possible as firms get geographically concentrated within a particular location; hence, this enables knowledge travel among firms, which in turn invigorates growth for the industries and regions. Jacob's theory, on the other hand, focuses on knowledge spillovers as diversity—diversity in industries fosters growth better than specialization, because more diverse perspectives encourage a greater exchange of ideas. As a result, diverse industries with geographic proximity generate more innovations and industrial growth compared to specialized industries (Glaeser et al. 1992).

Porter (1996) supports MAR's theory in that geographically concentrated industries accelerate growth. However, he argued that local competition, rather than local monopoly, fosters innovation. Competition, as Porter further claimed, exhilarates the pursuit and adaption of innovation.

Glaeser et al. (1992) pioneered further research on knowledge spillovers. These authors assumed that knowledge spillovers at the regional level are the key drivers of innovation and economic growth. More specifically, Glaeser et al. presumed that sectors in different geographical locations have different growth rates because of different types of spillovers between regions (intrasectoral spillovers versus intersectoral spillovers). In addition, local competitions between regions may as well differ. The model framed by Glaeser et al. (1992) examined three types of spillovers to measure the effects of knowledge spillovers on employment growth. Other studies, as discussed next, have utilized different approaches and indicated diverged results regarding the effects of specialization, diversity, and competition on employment growth.

Using employment growth as an indicator of economic performance, empirical results show that diversity is positively related to growth while specialization is negatively related, conforming to Jacobs' theory of diversity (Glaeser et al. 1992; Combes 2000; Deidda et al. 2003; Van Oort 2007). However, as far as industry development is concerned, the effects of diversity and specialization may indicate numerous outcomes Henderson et al. (1995) discovered that specialization has a positive effect on the performance of mature industries (traditional industries), whereas both specialization and diversity trigger beneficial aftermaths for high-technology industries (associated with new industries). By classifying sectors using Henderson et al.'s (2001) definition, Khoirunurrofik (2018) found that, in Indonesia, both specialization and diversity are positively correlated with traditional industries performance because the vast majority of traditional industries in Indonesia are small-scale enterprises that require diverse information from multiple industries to thrive. Additionally, competition was found to positively affect employment growth in industrial sectors (Glaeser et al. 1992; Paci and Usai 2001; Deidda et al. 2003; Almeida 2007; De Vor and De Groot 2010).

The above studies clearly suggest that agglomeration is positively related to industries regardless of their characteristics. One such industrial features is the technological intensity (Heidenreich 2009; Hartog et al. 2012; Liang and Goetz 2018). In recent studies on industrial development, technological intensity is generally associated with industrial lifecycle (Duranton and Puga 2001), learning patterns and competitive strategies (Hartog et al. 2012). These studies imply that agglomeration has various beneficial consequences on industries' technological intensity. High-technology industries obtain a high value from the creation and exchange of new ideas, acquired from an environment/area with diversified industries and various technology networks. Moreover, these industries focus on product innovations as the main goal. The diversity experienced by high technology facilitates learning processes from knowledge spillovers to increase product innovations, then create new products and new markets leading to increased labor absorption (Heidenreich 2009; Hartog et al. 2012; Liang and Goetz 2018).

In contrast, low- and medium–low-technology industries focus on innovation of production processes (Pavitt 1984; Hartog et al. 2012). According to Pavitt (1984:), low-technology industries are inclined to be "supplier dominated sectors." Innovation in such sectors/industries is aimed at efficiency and cost minimization by improving the technology of the production process. Therefore, more specialized industries that utilize similar production technology tend to be more suitable for low-technology industries (Liang and Goetz 2018). Previous studies (Heidenreich 2009; Hartog et al. 2012; Liang and Goetz 2018) have proved that related variety/diversity brings positive impacts on high-technology industries. Henderson et al. (1995) found that industries that incorporate relatively high technology (new industry) benefit from specialization and diversity, while industries with lower technology (mature industry) only benefit from specialization. Khoirunurrofik (2018) mentioned that Indonesian lower technology industries require both specialization and diversity to expand because of the domination of small enterprises in the low-technology industries. Therefore, these enterprises demand a wide variety of knowledge domains and information to advance.

As already noted, competition is deemed another agglomeration-based advantage apart from specialization and diversity (Porter 1996). The effects of competition on industries might also vary depending on the technological intensity employed by industries because technology is the driving force of competition (Porter 1985). Moreover, Glaeser et al. (1992) stated that competition, which occurs as the process of imitating new technology, encourages firms to innovate. Firms that do not develop their technology are displaced by more innovative ones. Hence, it can be deduced that industries employing high technology become more competitive, enabling them to produce more innovation and attain higher growth. This connects with a theory of knowledge spillovers which is discussed next.

Acs et al. (2013) introduced the knowledge spillover theory of entrepreneurship (KSTE). Knowledge spillovers are considered an impetus for new firm formation, which in turn enhances employment. According to Ghio et al. (2015), KSTE studies focus on the discussion of knowledge as the main input and resource for a firm's economic activities. In addition, another major component of KSTE is agglomeration economies in the form of specialization and diversity. Ghio et al. (2015) also stated that incumbent firms or research institutions such as public and private universities are the sources of knowledge in the KSTE field. The types of knowledge consist of codified knowledge, such as patents, publications, and citations, as well as tacit knowledge in the form of human capital.

Knoben et al. (2011) compared the influence of local knowledge sources and agglomeration economies on the formation of new firms in the Netherlands in 1999–2006 and found that traditional factors, such as economic growth and agglomeration economies (localization and urbanization economies) had a strong effect on the formation of new firms. The authors further maintained that local knowledge-based factors, such as research and development (R&D) intensity, level of education, and the presence of universities in an area were not significant.

Referring to KSTE, the study indicated that the positive influence of the regional knowledge base disappears when agglomeration economies are involved.

In Indonesia, data related to knowledge, such as R&D intensity, patents, and citations are still limited. This is the reason for using human capital proxies (as tacit knowledge) to describe the local knowledge base. Like agglomeration economies, human capital also has different impacts on employment growth based on the technological intensity in industries, because the so-called knowledge-based industry depends more on human capital than other factors (Chang et al. 2016). Previous studies (Simon 1998; Goetz and Han 2020) have found a positive effect of human capital on employment growth.

3 Research methods

Our data were collected from the Indonesia Annual Industrial Manufacturing Survey conducted by Indonesia Statistics in 2010 and 2015. The data comprised the number of workers and labor expenses in a firm. Data on human capital (percentage of population aged 15 and above and university graduates) were obtained from the National Socio-Economic Survey for 2010. Firms' age data were obtained from the survey data of 2006 (the year when the firm was operational), because the year of establishment data was available only in that year. Considering that industrial age is an important variable related to industrial lifecycles, firms in 2010 with no year of incorporation data were excluded.

In 2010 and 2015, there were 2019 data points of International Standard Industrial Classification) of all Economic Activities two-digit numerical codes for manufacturing industries in all districts/cities of Indonesia. The data of 294 districts/cities were collected, including the newly expanded districts/cities/provinces. In addition, some adjustments were made to the 2010 and 2015 data set due to the adjustment to the 2009 ISIC from the 2005 ISIC by Indonesia Statistics.

3.1 Data description/variables

The dependent variable in this model is the same as the one used by Glaeser et al. (1992): the employment growth in the two-digit industrial group i in region r (district/city) between 2010 and 2015, in the form of logarithmic values for a comparison between the number of workers in 2015 and 2010. The following variables are measured using 2010 as the base year:

$$y_{i,r10-15} = \ln\left(\frac{\mathrm{empl}_{i,r,2015}}{\mathrm{empl}_{i,r,2010}}\right). \tag{1}$$

The specialization index is measured using the model developed by Glaeser et al. (1992) and Combes (2000); it is the ratio/share of the number of workers in industry i in region r divided by the ratio of employment at the national level, as shown below:

$$\text{spe}_{i,r} = \frac{\text{empl}_{i,r/}\text{empl}_r}{\text{empl}_i/\text{empl}}. \tag{2}$$

Here, empl_r and empl denote the total number of workers in region r and at the national level, respectively, while $\text{empl}_{i,r}$ denotes employment in industrial sector i in region r and empl_i denotes employment in industrial sector i nationally. If the value of the specialization index is greater than 1, an industry in a particular region is more locally specialized than other regions in Indonesia. If the results show that specialization has positive effects on employment growth, it can be inferred that knowledge spillovers are formed within similar industries and play a central role in employment growth.

In terms of diversity, we refer to the calculation using the diversity index (Marrocu et al. 2013; Khoirunurrofik 2018, as illustrated below:

$$\text{Div}_{i,r} = \frac{1}{\sum_{\substack{i' \\ i \neq i'}} \left(\frac{\text{empl}_{i',r}}{\text{empl}_r - \text{empl}_i}\right)^2}. \tag{3}$$

A high value of diversity indicates that a region is relatively more diverse than other regions in Indonesia. If knowledge spillovers occur within different industries, then diversity plays a vital role in positively affecting employment growth. The other variable is the level of competition, calculated using Combes (2000) formula. Competition index is calculated by comparing the inversion of the local Herfindahl index using firm-level data (firm = f) and the inversion of the national Herfindahl index using regional industry data:

$$\text{Comp}_{i,r} = \frac{1/\sum_{f,i,r}(\text{empl}_{f,i,r}/\text{empl}_{i,r})^2}{1/\sum_i(\text{empl}_{i,r}/\text{empl}_i)^2}. \tag{4}$$

A competition index value exceeding 1 indicates that industry i in region r is locally more competitive than in other regions. If competition has a positive effect on employment growth, it shows that competition in the industry encourages innovation and employment growth.

To represent human capital variables, we use the percentage of the total population that has at least a non-degree diploma qualification (minimum 1 year) against the total working age population (aged 15 and above) in a region. The first control variable is the industrial wage rate based on the base year of measurement. The industrial wage rate is obtained by dividing the amount of employment payroll, and using weighted wage, we calculate the proportion of production and non-production workers employed in an industry.

$$\text{Wage}_{i,r} = \frac{(\text{Wage}_{p,i,r} \times \text{Empl}_{p,i,r}) \times \left((\text{Wage}_{\text{np},i,r} \times \text{Empl}_{\text{np},i,r}\right)}{\text{Empl}_{i,r}}. \tag{5}$$

$\text{Wage}_{i,r}$ is the weighted average wage of an industry in region r, $\text{Wage}_{p,i,r}$ is the average wage of production workers employed in industry i of region r. $\text{Empl}_{p,i,r}$ is the proportion of production workers in the total employment in industry i of region r. $\text{Wage}_{\text{np},i,r}$ is the average wage of nonproduction workers working in industry i of region r. $\text{Empl}_{\text{np},i,r}$ is the proportion of non-production workers in the total employment in industry i of region r.

Another factor used as a control variable is the average age of industry within a particular region. Agiomirgianakis et al. (2006) found that the age of firm/industry negatively and statistically significantly affects employment growth. Firms/industries in the early stage of development have a greater potential to generate job opportunities than firms/industries in a more mature stage.

The last control variable is foreign direct investment (FDI) in a particular region. This variable is strongly attributed to knowledge spillovers, as industries building strong international relations are deemed to acquire improved competitiveness and foster knowledge transfer.

3.2 Empirical specifications

The methods and empirical specifications employed in this study are a modification of the specifications designed by Glaeser et al. (1992), Combes (2000), and Ercole and O'Neill (2017). The empirical specification (basic model) that we designed is:

$$\begin{aligned}\ln\frac{\text{empl}_{i,r,2015}}{\text{empl}_{i,r,2010}} &= \alpha_0 + \beta_1 \ln \text{SPE}_{i,r} + \beta_2 \ln \text{COMP}_{i,r} \\ &\quad + \beta_3 \ln \text{Div}_{i,r} + \beta_4 \ln \text{Age}_{i,r} + \beta_5 \ln \text{Wage}_{i,r} \\ &\quad + \beta_6 \ln \text{Univ}_r + \beta_7 \ln \text{FDI}_r + \varepsilon_{i,r}.\end{aligned} \tag{6}$$

$\ln\frac{\text{empl}_{i,r,2015}}{\text{empl}_{i,r,2010}}$ is the log ratio of number of workers in industry i and region r in 2015 and 2010, $\text{Wage}_{i,r}$ is the wage rate in industry i in region r (in million rupiah), $\text{SPE}_{i,r}$ is the specialization index of industry i in region r (MAR's externalities), $\text{COMP}_{i,r}$ is the competition index in industry i in region r (Porter's externalities) , $\text{Div}_{i,r}$ is the degree of diversity in industry i in region r (Jacob's externalities) , Univ_r is the percentage of population that are university graduates (at least 1 year non-degree diploma qualification) in the total working age population , $\text{Age}_{i,r}$ is the Average age of industry i in region r (year) , FDI_r is the total foreign direct investment in region r (million rupiah).

To examine the hypothesis regarding the distinct effects of knowledge spillovers based on technological intensity, Eq. (6) is estimated using an industry classification dummy based on OECD's (2011) definition of technological intensity. According to this definition, there are four groups of industries based on the technological intensity in an industry: low-technology, medium–low, medium–high, and high-technology industries. However, Indonesia has only a few high-technology industries; therefore, their observations will be merged with medium–high-technology industries. The industrial grouping is presented in Appendix. Subsequently, Eq. (6) is modified as follows:

$$\begin{aligned}\ln\frac{\mathrm{empl}_{i,r,2015}}{\mathrm{empl}_{i,r,2010}} = \alpha_0 &+ \sum_{j=1}^{2}\alpha_j D_j + \beta_1\ln\mathrm{SPE}_{i,r} + \beta_2\ln\mathrm{COMP}_{i,r} \\ &+ \beta_3\ln\mathrm{Div}_{i,r} + \beta_4\ln\mathrm{Univ}_r + \beta_5\ln\mathrm{Wage}_{i,r} + \beta_6\ln\mathrm{Age}_{i,r} \\ &+ \beta_7\ln\mathrm{FDI}_r + \sum_{j=1}^{2}\beta_{8,j}D_j\times\ln\mathrm{SPE}_{i,r} + \sum_{j=1}^{2}\beta_{9,j}D_j\times\ln\mathrm{Div}_{i,r} \\ &+ \sum_{j=1}^{2}\beta_{10,j}D_j\times\ln\mathrm{COMP}_{i,r} + \sum_{j=1}^{2}\beta_{11,j}D_j\times\ln\mathrm{Univ}_r + \varepsilon_{i,r}.\end{aligned} \tag{7}$$

D_j/Dummy, j is industrial grouping based on technological intensity: low-technology industry, medium–low-technology industry, and high-technology industry (using one group of industries as the base).

The analysis was conducted using ordinary least squares (OLS) with a cross-sectional dataset. Regression was run to analyze industry data across all districts/regions in Indonesia in the year of 2010 and 2015, using 2009 ISIC two-digit numerical codes for manufacturing industries as the base. In the estimation process, we tested multicollinearity with VIF method and heteroscedasticity with Breusch–Pagan test. The heteroscedasticity test shows a p value <0.005, H_0 is rejected, which indicates that there is heteroscedasticity or the circumstances in which standard error of variables are non-constant. Although heteroscedasticity does not cause a bias in the coefficient estimates, it makes them less accurate or inefficient. Therefore, we used a heteroskedasticity-robust standard error to overcome this issue.

4 Results and analysis

4.1 Descriptive analysis

In total, there were 2019 industries in Indonesia (294 districts/cities) based on ISIC two-digit numerical codes of 2010. The vast majority of data comprise traditional industries, totaling 1129 industries (56%). There are 514 medium–low industries (25%) and 376 high-technology industries (19%).

The average value of the industrial variables: employment growth, degree of specialization, level of competition, diversity index, wage rate, and age of industry are presented in Table 1. Degree of specialization, level of competition, and diversity index are classified based on technological intensity incorporated in the industry according to the purpose of this study.

As shown in Table 1, aggregately, employment growth in the period of 2010 and 2015 was positive. The value of specialization and diversity is greater than 1, which implies that Indonesian industries have relatively high specialization and high diversity. The competition index value of 0.24 shows that the level of competition within similar industries in Indonesia is relatively low.

Based on the technological intensity in the industry, the specialization index is the highest in medium–low-technology industry (3.78), second highest in the

Table 1 Average value of aggregate industrial variables across different industries in Indonesia in 2010

Variables	Unit	Obs	Mean	Std dev	Coefficient of variance	Min	Max
Dependent							
Employment growth (2010–2015)	Natural Log Ratio	2019	0.2	0.98	4.9	−5.57	6.16
Independent							
Industry level							
Specialization	Index	2019	3.15	10.93	3.47	0.03	309.09
Competition	Index	2019	0.24	0.56	2.33	0.01	14.37
Diversity	Index	2019	4.15	2.92	0.7	1.00	13.82
Weighted wage	Million (IDR)	2019	9.94	12.83	1.29	0.02	465.60
Average age	Years	2019	19.03	9.78	0.51	4.00	100
Regional level							
Percentage of university graduates	%	294	7.15	4.42	0.62	1.15	26.09
Foreign direct investment	Million (IDR)	294	461,757	2,240,864	4.86	0	2.5×10^7

low-technology industry (3.01), and lowest in high-technology industry (2.69). In terms of the competition index, both the low- and medium–low-technology industries have a value of 0.22, while the high-technology industry has the highest value of 0.35. These findings are reasonable since a high level of specialization indicates the presence of a monopoly rather than competition in similar industries, as argued by the MAR's theory of job specialization. A relatively higher competition level found in high-technology industries is because high-technology firms require more innovations to maintain their presence in the market than firms with low technology. This is in accordance with Porter's theory that competition fosters innovation and growth.

The diversity index shows a similar pattern to the competition index, in which the lowest diversity is found in industries harnessing low technology, while the opposite is found in high-technology industries where the diversity index is high. Such inclinations show that industries harnessing lower technology are more specialized, while industries harnessing high technology are more diverse and competitive. Further illustrations of specialization, competition, and diversity are illustrated in Figs. 1, 2 and 3.

The average industrial wage is Rp. 9.95 million per year. Note that the average industrial wage is weighted using the proportion of production workers and non-production workers; therefore, the value might be lower than the normal average calculation. Those working in high-technology industries earn the highest wage, while those working in low-technology industries earn the lowest. This is because high-technology industries (tech-intensive) require workers with a higher set of skills than low-technology industries that are inclined to be labor intensive.

The average age of industry in Indonesia is 19.04 years, indicating a fairly old age. Observing by industrial grouping, traditional industries have the lowest average

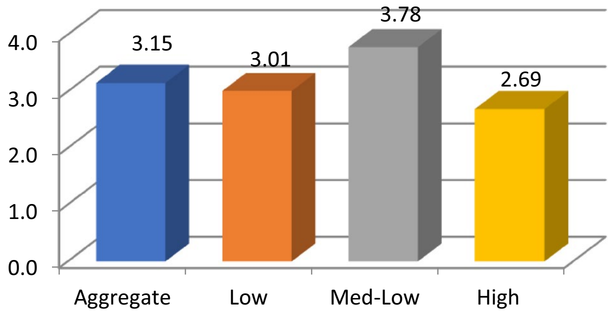

Fig. 1 Specialization based on technological intensity in industry

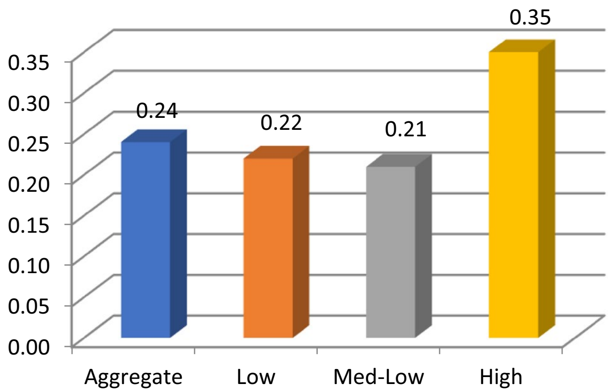

Fig. 2 Competition based on technological intensity in industry

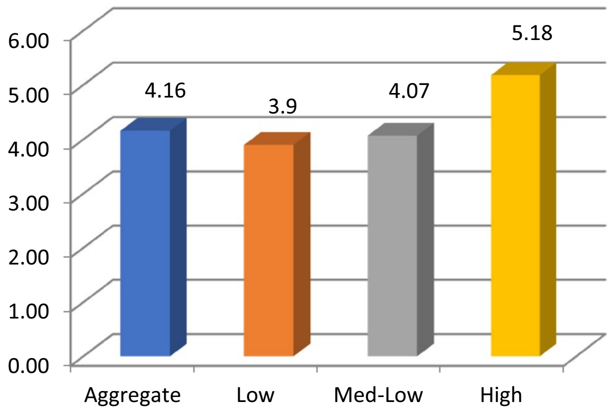

Fig. 3 Diversity based on technological intensity in industry

Table 2 OLS results: basic model

Variables	Emp growth
Specialization (Sp)	− 0.1529***
Competition (Comp)	− 0.0306
Diversity (Div)	− 0.00579
Wage	0.1036***
Age	− 0.1157**
University (Univ)	− 0.0111
Foreign investment	− 0.0090**
Cons	0.3400***
Adjusted R^2	0.0717
N	2019

Estimation using robust standard errors; All variables are in natural logarithmic form

Significance level: $*p<0.10$, $**p<0.05$, $***p<0.01$

age, while high-technology industries have the oldest. This is an intriguing phenomenon, as traditional industries usually tend to have a relatively mature age, while high-technology industries tend to be newly established. This shows that, in Indonesia, the majority of newly established industries are classified as traditional rather than high-technology industries, because the establishment of a high-technology industry requires a greater capital investment and highly skilled workers.

This factor seems to be the cause of relatively higher employment growth in traditional industries than in other industry groups, because the majority of newly established industries fall under the traditional classification. The average variable of human capital, which is the percentage of graduates with a high level of education, is relatively low, only 7.15% of the total working-age population (15 years and above).

4.2 Empirical results

This section presents the empirical estimates of the basic model and technological intensity. In general, the analyses of these components suggest various outcomes depending on types of industries.

4.2.1 Basic model estimation

The regression results without the interaction of industrial technology using OLS is shown in Table 2. In the second column, regression results from the basic model (regression without considering technological intensity) are presented. The basic model estimation results indicate that specialization negatively and statistically affects employment growth significantly. The higher the industry specialization, the lower the employment growth.

Based on the definition of the elasticity and estimated results are shown in Table 2 (elasticity of specialization is −0.15), it can be inferred that a 1% increase in industry specialization decreases the 5-year employment growth rate between 2010 and 2015 from 22.14[2] to 21.99%. This result is in line with that of other studies (Glaeser et al. 1992; Bishop and Gripaios 2010; Ercole and O'Neill 2017; Khoirunurrofik 2018).

Competition, diversity, and human capital have negative effects on employment growth, yet they are statistically insignificant. There is a slight contrast with previous studies (Glaeser et al. 1992; Khoirunurrofik 2018), which also found that diversity, competition, and human capital have statistically insignificant negative effects on employment growth. Another factor with a positive relationship with employment growth is the wage rate. The higher the wage rate, the higher the employment growth. This is because workers prefer industries/regions that offer relatively higher wage rates, which reveals that Frenken et al. (2007) findings are confirmed.

Foreign investment has a negative effect on employment growth. This finding is in contrast to the results of Lipsey et al. (2010) and Inekwe (2013), who discovered that foreign investment positively affects employment growth. It seems that most foreign investments are allocated for capital-intensive industries; thus, workers are replaced, in the end, leading to decreased demand for workers. The age of industry negatively affects employment growth. This finding is corresponding to the conclusions from Agiomirgianakis et al. (2006) as earlier established industries have reached a maturity stage, and therefore, require less development compared to newer ones.

4.2.2 Estimates based on technological intensity

In this estimation model (full sample is given in the second column of Table 3), we used low-technological-intensity industries as the base, and the values for medium–low and high industries are net effects. The comparison was conducted between two industry groups: low industries and medium–low industries; low industries and high-technology industries. The comparison between medium–low industries and high industries was not included, because it shows no significant difference regarding the effects of externalities of agglomeration and human capital on employment growth. To probe further our observation, as shown in the dummy coefficients (D2 and D3) in the table, the results are insignificant. This shows that if other independent variables are constant, there is no difference in the average employment growth between these three industry groups that have different levels of technological intensity. The difference between industry groups based on technological intensity lies in their influence on the effects of knowledge spillovers on employment growth, as explained in our initial hypothesis.

[2] Five-year employment growth between 2010 and 2015 in percentage form. Estimated from inverse of natural logarithm of employment growth.

Table 3 OLS results: the effects of technological intensity

Variables[a]	Emp growth		
	Model 1[b]	Model 2[c]	Model 3[d]
Specialization (Sp)	−0.1413***	−0.1411***	−0.1547***
Competition (Comp)	−0.052*	−0.0524*	−0.0236
Diversity (Div)	0.019	0.0017	−0.0038
Wage	0.1151***	0.1151***	0.1187***
Age	−0.1016**	−0.0969**	−0.1089**
University (Univ)	−0.1017**	−0.0161	−0.1032**
Foreign investment	−0.094**	−0.0093**	−0.0091**
D2 × Sp	−0.0335	−0.0354	–
D2 × Comp	0.0474	0.0443	–
D2 × Div	−0.0491	−0.0144	–
D2 × Univ	0.1769**	–	0.1778**
D3 × Sp	−0.0433	−0.0433	–
D3 × Comp	0.1298**	0.1392**	–
D3 × Div	−0.0633	−0.0356	–
D3 × Univ	0.2180**	–	0.2370**
D2	−0.3135	−0.0303	−0.4751***
D3	−0.2168	0.1866	−0.5593***
Cons	0.4252**	0.2696	0.5285***
Adjusted R^2	0.0776	0.0751	0.0779
N	2019	2019	2019

Estimation using robust standard errors; All variables are in natural logarithmic form

Significance level: *$p<0.10$, **$p<0.05$, ***$p<0.01$

[a]D2: Medium–low-technology industries; D3: High-technology industries; D1: Low-technology industries as the base

[b]Full sample

[c]Interaction between technology intensity and agglomeration model

[d]Interaction between technology and human capital

4.2.3 Specialization

Similar to the results of the basic model, specialization also has negative effects and significant to employment growth on low-technology industries (as the base), and the elasticity is −0.14. It implied that a 1% increase in industry specialization would yield a 0.14% decrease in the 5-year employment growth rate between 2010 and 2015. The dummy coefficients of interaction between specialization and technological intensity in medium–low- and high-technology industries are found to be insignificant. This means that there is no difference in the effects of specialization on employment growth in both industry groups. The impact of specialization in all three industry groups is negative (−0.141). This contrasts with MAR's theory stating that specialization provokes employment growth. However, many studies have found similar empirical findings as ours, including Glaeser et al. (1992), Combes (2000), Bishop and Gripaios (2010), Ercole and O'Neill (2017), Khoirunurrofik (2018), and Liang and Goetz (2018). However, our study contradicts the findings of Henderson et al. (1995) and Liang and Goetz (2018), who found positive effects of specialization on employment growth in low-technology industries.

Negative effects of specialization seem to occur due to the contradictory effects of specialization (Bishop and Gripaios 2010; Liang and Goetz 2018). On one hand, local concentration of similar firms (specialization) in a particular region prompts positive effects of MAR's externalities, which can drive efficiency and improve productivity. On the other hand, overspecialization increases costs and generates diminishing returns, leading to a decline in employment growth. Furthermore, according to Bishop and Gripaios (2010), high specialization leads to an increase in productivity, which can replace labor needs. Khoirunurrofik (2018) also stated that traditional manufacturing has the characteristics of inelastic price of demand; hence, increasing productivity will reduce employment growth. The data in Table 3 support this that in 2010, 55% of industries in Indonesia were dominated by low-tech (traditional) industries. In addition, Table 3 also presents the increased trend in the 2011 and 2015 where labor productivity in the manufacturing industry experienced a fairly high increase of 11% in 2011, 6.4% in 2012, 25.97% in 2013, and 10.63% in 2014, and 10.67% in 2015. The highest labor productivity was in 2015 (Indonesia Statistic 2017).

4.2.4 Competition

Competition has negative and significant effects on employment growth in low-technology industries and the elasticity is -0.052. It means a 1% increase in the competition index decreases the 5-year employment growth rate between 2010 and 2015 from 22.14 to 22.09%. The interaction between the medium–low-tech industry dummy and competition demonstrates insignificant results; this shows that there is no difference in the effect of competition between low-tech industries and medium–low-tech industries. Conversely, the interaction between competition and the high-tech industry dummy shows positive and significant effects. It seems that there is a difference in the effects of competition on employment growth, where the effects are larger in high-technology industries than in low-technology industries. These findings are in proportion to that of Porter (1985) and Porter (1996), who found that technology and agglomeration stimulate competitive advantage. Consequently, innovation and industrial growth are spurred. The results also indicate that the more advanced the technology incorporated in the industry, the higher the level of competition (in accordance with what is described in the descriptive analysis). This additionally provides positive effects on employment growth. Glaeser et al. (1992) mentioned that the development of new technology attracts other firms in similar industries to compete by imitating and improving the newly invented technology. Thus, more innovation and growth are generated. Firms that refrain from competing and experience sluggish technology development perish.

4.2.5 Diversity

The results show that diversity does not significantly influence employment growth on all levels of technological intensity in industry.

4.2.6 Human capital

The effects of human capital in low-technology industries are negative and significant. This could indicate that low-technology industries no longer require high-quality human capital. A high wage rate commonly associated with high-quality human capital decreases demand for workers in low-tech industries.

Nevertheless, the interaction between the medium–low-technology industry dummy and the high-technology industry dummy with the human capital variable shows positive and significant effects. It indicates that there is a different effect of human capital on low-technology industries and high-technology industries. The effects of human capital on employment growth increase as the technological intensity of industries become more advanced. A 1% increase in human capital increases 5-year employment growth of medium–low-technology industries between 2010 and 2015 from 22.14 to 22.22% and increases high-technology industries to 22.26%. This shows that the higher the technological intensity of the industries, the higher the quality of human capital required. Therefore, our findings reveal that human capital has a bigger impact on employment growth in both medium–low and high-technology industries, which accords with Simon's (1998) finding on the positive effects of human capital on employment growth. In addition, our results corroborate Chang et al. (2016) statement that high-technology industries are classified as knowledge-based industries requiring high-quality human capital. As Table 3 shows Models 2 and 3 present the difference in specifications by excluding the interaction between technology intensity and human capital (Model 2 in column 3) and the interaction between technology intensity and agglomeration externalities (Model 3 in column 4). Table 3 also presents the results of estimates that are consistent in terms of signs although they differ at the level of significance.

5 Conclusion and recommendations

This study estimates the effects of externalities of agglomeration, in the form of knowledge spillovers and externalities obtained from human capital on employment growth. Specifically, this study analyzes the effects of the aforementioned factors based on the technological intensity of an industry. The data were obtained from ISIC two-digit numerical codes for manufacturing industries based on the 2009 Indonesian Standard Industrial Classification covering regions/cities in Indonesia in 2010 and 2015.

We use OLS, with employment growth as the dependent variable, and specialization index, competition index, diversity index, and human capital represented by the percentage of university graduates as the main variables. From the estimation using interaction with technological intensity, specialization has negative and significant effects on employment growth; similar effects are found in all three industry groups. The effects of specialization based on technological intensity is −0.14. The effects of diversity also show similar effects in the three industry groups. Diversity has positive yet insignificant effects on employment growth in all industry groups.

Competition has different effects based on the technological intensity of the industry. In low-technology industries, competition decreases employment growth and the elasticity is −0.052. Furthermore, the effects of competition in high-technology industries are different from those in low-technology industries and have a positive net effect, amounting to 0.078. From these values, it can be deduced that the effects of competition on employment growth are positive and increase as technology increases and vice versa in low-technology industries.

Human capital has different effects on employment growth between low- and medium–low-technology industries and between low-technology and high-technology industries. In low-technology industries, the effects of human capital are negative and significant, amounting to −0.10. In medium–low-technology industries, the net effect of human capital on employment growth is 0.075. In high-technology industries, the value of the net effects of human capital on employment growth is higher, at 0.17. These results indicate that human capital reduces employment growth in low-tech industries and increases employment growth in low–medium- and high-tech industries. The results of this study confirm Khoirunurrofik's (2018) findings, where in addition to the competition, human capital also has a different role and increases with increasing industrial technology intensity.

The findings of this study have several policy implications. First, the government should encourage competition in low- and medium–low-technology industries. This refers to the results that show that competition has a positive effect on employment growth in high-technology industries that have a higher competition index than other industry types. Second, the government needs to support increased opportunities for the community to achieve minimum university education, which is proven to have a positive influence on employment growth in the manufacturing industry.

This study has some limitations, which can be considered for conducting further research. First, this study does not consider the possibility of endogeneity in the estimation model. Thus, attention to such a matter should be an area of emphasis. Second, with regards to the data used to represent the human capital variable, the estimation could have been better using the proxy of the number/percentage of workers in manufacturing industries by educational attainment. Hence, the development of this area would be a priority.

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Appendix

See Table 4.

Table 4 Industrial grouping based on technological intensity. Source: the 2011 Organisation for Economic Co-operation and Development (OECD) definition

High-technology industries	Medium–high tech
Aircrafts and spacecrafts	Electrical machinery and apparatus
Pharmaceuticals	Motor vehicles, trailers, and semi-trailers
Office, accounting, computing machinery	Chemicals excluding pharmaceuticals
Radio, TV, and communication equipment	Railroad and transport equipment
Medical, precision, and optical instruments	Machinery and equipment
Medium–low technology	Low-technology industries
Building and repairing of ships and boats	Manufacturing n.e.c; recycling
Rubber and plastic products	Wood, pulp, paper, paper products, printing, and publishing
Coke, refined petroleum, and nuclear fuel	Food products, beverages, tobacco
Other non metallic mineral products	Textile, textile products, leather, and footwear
Basic metals and fabricated metals	

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