4. HUMAN CAPITAL AND FIRM INNOVATION: NEW EVIDENCE FROM ASEAN COUNTRIES

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Abstract

The study explores the role of human capital in firm innovation in the ASEAN countries. Different ordinal logistic regression models are utilized to estimate the data set from the World Bank's Enterprise Surveys. The results show evidence supporting the positive role of general human capital (i.e., employee general education and top manager's prior work experience in the current sector) in the likelihood of firm innovation at a higher degree of radicalness. Furthermore, specific human capital (i.e., employee training) is also positively related to the propensity to innovate at a higher level of radicalness. Given the results, the study suggests that there should be more investments in training, especially formal training for employees at the firm level, and at the macro level; the governments should channel more resources into education to boost innovation.

Keywords: ASEAN, education, human capital, innovation, training

JEL Classification: J24, L60, O32

1. Introduction

Firm-level innovation is the research topic that has attracted a great deal of attention in the literature (Coad, Segarra, & Teruel, 2016; Moagăr-Poladian, Folea, & Păunică, 2017; Pelinescu, Pauna, Saman, & Diaconescu, 2019; van Uden, Knoben, & Vermeulen, 2017). Among different aspects related to innovation, the relationship between human capital and innovation is an interesting research theme that has been extensively investigated (Fonseca, de Faria, & Lima, 2019; Gallié & Legros, 2012; McGuirk, Lenihan, & Hart, 2015; OECD, 2011; Santi & Santoleri, 2017). Human capital is important for firm innovation because well-educated workers can invent or improve new technologies and exploit technological

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progress (Lundvall & Johnson, 1994). Firms' human capital consists of different dimensions, at both the managerial level and the firms' general workforce (Gallié & Legros, 2012; Kato, Okamuro, & Honjo, 2015; Protogerou, Caloghirou, & Vonortas, 2017; Sun, Li, & Ghosal, 2020). Nevertheless, empirical studies taking into account various dimensions of human capital (at both the employee and founder/manager levels) in the relationship with firm innovation are limited, especially in the context of developing countries (Sun *et al*., 2020). Hence, the objective of this study is to fill this gap by investigating the role of different dimensions of human capital in firm innovation in ASEAN.

The geographical focus of the study is the ASEAN (Association of South East Asian Nations) countries. ASEAN has a population of 650 million people and is a fast-growing region with a nominal GDP of US$ 2,891 billion (constituting the world's fifth-largest economy) (IMF, 2018). In ASEAN, the engine of growth relies mainly on low-wage and labor-intensive manufacturing. However, this is not sustainable because of the wage increase and severe competition from the international market. To effectively deal with such challenges, the ASEAN economies are paying more attention to innovation as a new engine of economic growth, and human capital is considered an important determinant of this innovation development (ERIA, 2018). Therefore, it is interesting to examine the role of human capital in firm innovation in a fast-growing region like ASEAN.

This research contributes to the literature in three important ways. First, to the best of the authors' knowledge, there has been no study investigating this topic in the ASEAN context. Therefore, it contributes to the literature as the first comprehensive research on the role of human capital in firm innovation in ASEAN.

Second, while a significant body of research has examined this stream of research with a focus on employees (e.g., Bauernschuster, Falck, & Heblich, 2009; Gallié & Legros, 2012; González, Miles-Touya, & Pazó, 2016; McGuirk *et al*., 2015) or founders/managers (e.g., Kato *et al*., 2015; Marvel & Lumpkin, 2007) separately, very few empirical studies have investigated this research theme at both the employee and founder/manager levels (see Lund Vinding (2006) and Protogerou *et al*. (2017) for exceptions). To fill this gap, the current analysis considers both human capital groups, which will give an overall picture of human capital within the context of firm innovation.

Third, this is one of the few studies to comprehensively deal with the two most popular problems of ordinal regression models (*i.e*., the "parallel regression/proportional odds" assumption and the hierarchical structure of the data) in the innovation topic by using generalized ordered logit model (GOLM) and multilevel mixed-effects ordered logit model (MOLM). In particular, the GOLM (Williams, 2006) is utilized because it is more advantageous than the standard ordered logit model (OLM) in dealing with the "parallel regression/proportional odds" assumption that is often violated in the empirical studies. Furthermore, we also consider the hierarchical structure of the dataset using the MOLM, which is rarely examined in empirical studies on innovation at the firm level.

The remainder of the study is structured as follows: Section 2 surveys the theoretical and empirical literature on the role of human capital in firm innovation. Then the hypothesis development follows. In Section 3, we describe the data set and the econometric methods. In Section 4, we discuss the main results. The conclusions and implications follow in section 5.

2. Literature Review and Hypotheses

2.1 Related Concepts

2.1.1 Innovation

The seminal work of Schumpeter (1934), highlighting the importance of innovation in economic development, marked the inception of innovation as a fruitful and fashionable research area today (Fagerberg, Fosaas, & Sapprasert, 2012). He also introduced the definition of innovation that is still relevant to contemporary innovation research (Fagerberg *et al*., 2012; McGuirk *et al*., 2015). Specifically, Schumpeter (1934) defined innovation as the "new combinations" of existing knowledge and resources to come up with five types of innovation: (i) new products, (ii) new processes (or new methods of production), (iii) new materials (or resources), (iv) new markets, and (v) new organizations of an industry in terms of commerce, business, and finance (Fagerberg *et al*., 2012; McGuirk *et al*., 2015; Ziemnowicz, 2013). Since then, the innovation literature has developed significantly, evidenced by an increased number of publications and interest from diverse research disciplines. Along with this development, scholars have conceptualized different definitions of innovation (see Edwards-Schachter (2018), Fagerberg *et al.* (2012), and Tidd and Bessant (2009) for a review of innovation definitions). Despite various conceptualizations of innovation, most definitions share the idea that innovation is concerned with the adoption of a new idea or behavior (Jiménez-Jiménez & Sanz-Valle, 2011).

The current firm-level innovation literature is dominated by the innovation definition of the *Oslo Manual* (Gault, 2018). According to the *Oslo Manual,* innovation is defined as "the implementation of a new or significantly improved product (good or service), or process, a new marketing method, or a new organizational method in business practices, workplace organization or external relations" (OECD, 2005, p. 46). Based on this definition, innovation is classified into four types: (i) product innovation, (ii) process innovation, (iii) marketing innovation, and (iv) organizational innovation (OECD, 2005).

For this study, we use the definition of innovation based on the *Oslo Manual* (OECD, 2005) due to the popularity of this definition, and the methodology for measuring innovation activities of the *Oslo Manual* was used in the data source for our empirical analysis. Besides, in this study, we only concentrate on product innovation. As defined by the OECD (2005, p. 48), product innovation is "the introduction of a good or service that is new or significantly improved with respect to its characteristics or intended uses. This includes significant improvements in technical specifications, components and materials, incorporated software, user friendliness or other functional characteristics".

Furthermore, it should be noted that regarding the stages of innovation, innovation can also be categorized into "innovation input" and the result of this stage – "innovation output". Innovation input concerns the resources necessary for carrying out innovation, commonly expressed in R&D activities. Innovation output refers to the outcome of this process (*i.e*., product, process, marketing, and organizational innovation) (Coad *et al*., 2016; Kato *et al*., 2015; OECD, 2005; Rodil, Vence, & del Carmen Sánchez, 2016).

2.1.2 Human Capital

The seminal research by Becker (1964) defined human capital investments as "activities that influence future monetary and psychic income by increasing resources in people", and human capital is formed by formal schooling and on-the-job training. OECD (2001, p. 18) suggested a widely used definition of human capital: "the knowledge, skills, competencies and attributes embodied in individuals that facilitate the creation of personal, social and economic well-being".

Human capital can be categorized into "general (or generic)" and "specific" types (Becker, 1964; Protogerou *et al*., 2017). General human capital is concerned with the general knowledge gained from formal education and professional experience. Specific human capital is mainly acquired from training and is less transferable knowledge and skills that can be directly used in a smaller entrepreneurial context (González *et al*., 2016; Kato *et al*., 2015; Protogerou *et al*., 2017). At the firm level, most of the investment in human capital occurs by training for employees (Acemoglu, 1997). Similarly, OECD (2010, p. 9) suggested that "empowering people to innovate relies not only on broad and relevant education, but also on the development of wide-ranging skills that complement formal education".

2.2 The role of Human Capital in Firm Innovation

2.2.1 Theoretical Background

The resource-based view of the firm considers human capital a critical resource for firms to sustain competitive advantage and innovation *(Barney, 1991; Fonseca et al., 2019; Sun et al.*, 2020). Human capital is important for innovation because a creative labor force can develop and apply new ideas at both the micro level of firms as well as the macro level of the whole society (OECD, 2011). Lundvall and Johnson (1994) established that better education contributes positively to innovation via two channels: (i) higher educated employees can invent and improve new technologies, and (ii) they can also exploit technological progress. Blundell, Dearden, Meghir, and Sianesi (1999) also claimed that employees with better education and skills are an essential component of innovation.

An extensive review by OECD (2011) pointed out six channels through which human capital may boost innovation: "Generating new knowledge", "Adopting and adapting existing ideas", "Enabling innovation through a capacity to learn", "Complementing other inputs to innovation", "Generating spillovers", and "Adding to social capital". First, "Generating new knowledge" refers to the generation of knowledge by skilled employees, which helps spur innovation activities. Second, "Adopting and adapting existing ideas" indicates that high-skilled employees are good at absorbing technological knowledge, which can be applied to improving existing products or processes. Third, "Enabling innovation through a capacity to learn" implies that well-educated workers are more competent in learning new skills; hence, they have more ability to contribute to firm-level innovation. Fourth, "Complementing other inputs to innovation" means that skilled employees interacting with other inputs, for example, capital investment, can promote innovation. Fifth, "Generating spillovers" indicates that skilled workers generate "spillover effects", which indirectly contributes to innovation. For example, skilled workers may spread their know-hows in the workplace via interactions, or they can act as explicit or implicit role models, which consequently encourages the quicker human capital formation of other workers. Finally, "Adding to social capital" refers to the idea that high-quality human capital may contribute positively to social capital, and social capital can enhance trust and networking, which is essential for increasing the efficiency of innovation.

The role of absorptive capacity as a channel for human capital effects on firm innovation is also widely emphasized in previous research (Cohen & Levinthal, 1990; Murovec & Prodan, 2009). Absorptive capacity refers to "the ability of a firm to recognize the value of new, external information, assimilate it, and apply it to commercial ends" (Cohen & Levinthal, 1990, p. 128), which is “critical to its innovative capabilities” (Cohen & Levinthal, 1990, p. 128). Human capital practices, especially training, contribute significantly to strengthening the absorptive capacity (Cohen & Levinthal, 1990; Lund Vinding, 2006). As highlighted by Cohen and Levinthal (1990, p. 129), “firms also invest in absorptive capacity directly, as when they send personnel for advanced technical training”.

Firm-sponsored training increases a firm’s propensity to innovate. The reason is that training provides employees with state-of-the-art skills and technological knowledge. Hence, they can understand complex technologies, products, and production processes, contributing to firm-level innovation (Gallié & Legros, 2012; Protogerou *et al*., 2017). Furthermore, the world is now changing rapidly with science and technology developing at a fast pace, thereby leading to quick depreciation of human capital gained from formal education. Accordingly, learning by doing, in the form of in-firm training, brings efficiency gains and better adaptation to technical changes, which facilitates firms’ innovation efforts (Bauernschuster *et al*., 2009; Gallié & Legros, 2012).

Founders/managers’ human capital is also widely mentioned in the human capital–innovation literature (Kato *et al.*, 2015; Lund Vinding, 2006; Marvel & Lumpkin, 2007; Protogerou *et al*., 2017). Founders/managers’ human capital is vital for firms’ innovative processes for several reasons. First, regarding founders/managers’ general human capital *(i.e*., formal education or prior managerial experience), entrepreneurs’ higher educational attainments form better knowledge background to sense and seize chances for innovation available in the market (Protogerou *et al.*, 2017; Shane, 2000; Unger, Rauch, Frese, & Rosenbusch, 2011). In addition, experience breadth (i.e., working in various markets) can help firms identify innovative opportunities easier (Protogerou *et al*., 2017). Second, as for founders/managers’ specific human capital (*i.e*., prior experience of technologies or product/process innovations), for example, in universities or research institutes is supposed to be conducive to innovation. The reason is that they can appraise the feasibility of a particular research stream, develop R&D strategies, coordinate research projects, and access research networks with external organizations (Kato *et al*., 2015; Protogerou *et al*., 2017). Entrepreneurs’ human capital plays a particularly important role in the innovation process of start-ups or young firms because it makes up for deficiencies in human and physical capital, limited resources, severe information asymmetries, and weak networking relations at the start-up stage (Kato *et al*., 2015; Protogerou *et al*., 2017).

2.2.2 Empirical Literature

There have been many empirical studies on the role of human capital in firm innovation (*e.g*., Bauernschuster *et al*., 2009; Fonseca *et al*., 2019; Gallié & Legros, 2012; Kato *et al*., 2015; Lund Vinding, 2006; Marvel & Lumpkin, 2007; McGuirk *et al*., 2015). We explore the empirical literature in two aspects: human capital proxies and results.

Human Capital Proxies

The measurement of human capital at the firm level is diverse, and one of the most popular measurements is through the level of education or years of schooling (general education) (McGuirk *et al*., 2015). However, as pointed out by Mincer (1962), formal schooling is inadequate for building an efficient labor force because graduation from educational institutions only signifies the completion of a general and preparatory phrase, rather than the accomplishment of the training process. Accordingly, measuring human capital in terms of skills gained through training is an essential element to explore the role of human capital in firm innovation (Bauernschuster *et al*., 2009). Thus, the literature reveals two groups of human capital proxies in empirical studies: (i) general (or generic) human capital, (ii) specific human capital. General human capital mainly concerns the level of formal education or founders/managers' prior managerial experience. Specific human capital mainly involves employee training or founders/managers' prior experience of technologies or product/process innovations. Furthermore, the research subjects concentrate on two groups: (i) employees and (ii) founders/managers (Fonseca *et al*., 2019; Gallié & Legros, 2012; González *et al*., 2016; Kato *et al*., 2015; Lund Vinding, 2006; Marvel & Lumpkin, 2007; Protogerou *et al*., 2017).

Human capital can also be measured as a group of variables. For example, McGuirk *et al.* (2015) introduced the concept of "Innovative Human Capital", a group of four components: "education", "training", "willingness to change in the office", and "job satisfaction".

Results

The predominance of empirical literature considers human capital a crucial factor in enhancing innovation, with data much focusing on developed countries in Europe and the U.S.

Within the context of Europe, Lund Vinding (2006), employing data from 1,544 firms in Denmark in 1993–1995, found that the proportion of employees obtaining an academic degree is positively associated with innovation. Bauernschuster *et al.* (2009), using the dataset of 3,198 German enterprises during the period 1997–2001, found that firms' effort in providing continuous training with leading-edge knowledge significantly boosts their innovation probability. Gallié and Legros (2012) also pointed out that employee training is positively related to technological innovation based on the data of 993 French industrial firms during 1986–1992. McGuirk *et al.* (2015) introduced the concept of "Innovative Human Capital" (IHC) and investigated the effect on innovation performance. The dataset consists of 1,129 firms from the "Irish National Centre for Partnership and Performance 2009 Workplace Survey". The findings suggest that IHC is essential for the innovation performance of small firms with less than 50 workers.

González *et al.* (2016), employing data from 3,257 Spanish firms during the 2001–2011 period, established that implementing training for workers remarkably strengthens the probability of innovation. Protogerou *et al.* (2017), utilizing the dataset of 3,962 young firms (3 to 10 years in business) in ten European countries surveyed in 2010–2011, showed evidence that founders' educational attainment and previous R&D experience are positively connected with not only R&D expenses but also innovation outputs. Furthermore, employees having a university degree and employee training are positively associated with innovation outputs. Recently, Fonseca *et al.* (2019) studied a comprehensive dataset of 11,970 firms in three periods: 2006–2008, 2008–2010, and 2010–2012 in Portugal and found that the proportion of workers attaining the college level of education is positively associated with innovation outputs.

In the U.S. context, Marvel and Lumpkin (2007), based on the data of 145 incubator technology managers, indicated that entrepreneurs' formal education and former knowledge about technology have positive effects on the radicalness of innovation.

Some studies on this research topic focus on other regions such as China, Japan, Africa, or a group of countries (Kato *et al.,* 2015; Ma, Zhai, Zhong, & Zhang, 2019; Sun *et al*., 2020; van Uden *et al.,* 2017). Sun, Li, and Ghosal (2020), using a sample of 795 firms in 2000, 2002, and 2003 in China, concluded that human capital is important for patenting. In the Japanese case, Kato *et al.* (2015) investigated 389 Japanese start-ups in 2008 and found that founders' previous innovation experience has a direct positive effect on innovation outcomes. Additionally, founders' educational attainment has an indirect positive impact on innovation outcomes via R&D expenditure. In the context of Africa, van Uden *et al.* (2017) examined the role of different measurements for human capital (*i.e.*, staff school attainment, formal training within firms) in innovation performance of 8,223 firms of 13 nations in Sub-Saharan Africa covered by the *Enterprise Survey* of the World Bank. They found that training at the firm level to enhance human capital is more important for innovation performance than traditional factors such as school attainment and R&D. Ma, Zhai, Zhong, and Zhang (2019), based on the dataset of 304 manufacturing firms across 13 countries and regions, found that task-related training increases innovation.

Conversely, several studies showed a negative association between human capital and innovation (Lund Vinding, 2006; Marvel & Lumpkin, 2007; Protogerou *et al.*, 2017).

Lund Vinding (2006) indicated that the work experience of managerial personnel is negatively associated with innovation in science and Information Communication Technology (ICT) firms. The reason is probably that compared to the young, old people have more difficulty acquiring the latest technologies that are changing and updating very fast. Furthermore, the young nowadays are educated with the most updated knowledge about science and technology, which the old could not access in their time.

Marvel and Lumpkin (2007) showed that entrepreneurs' former knowledge about serving the market is negatively related to innovation radicalness. The possible explanation is that high knowledge about customers and markets may lead to the entrepreneurs' preconceived notions of the prospects (possibly risky) that may impede the likelihood that entrepreneurs would take risky innovation ventures.

Protogerou *et al.* (2017) found evidence that founders' general professional experience is negatively related to R&D expenditure. The reason could be that founders' formal education, which has a significantly positive effect on innovation, is more important for start-ups' innovation in comparison with general professional experience. Specifically, higher education level, not experience in this context, is an essential condition for the constant absorption of highly specialized knowledge that constitutes the basis for innovation.

The above-mentioned theoretical and empirical literature leads to three hypotheses in the ASEAN context as follows:

Hypothesis 1: Top manager's prior work experience is positively related to the likelihood of firm innovation.

Hypothesis 2: Employee general education is positively related to the likelihood of firm innovation.

Hypothesis 3: Employee training is positively related to the likelihood of firm innovation.

3. Data and Research Method

3.1 Data

The data for this research is taken from the World Bank's *Enterprise Surveys*. It is a large-scale survey of over 146,000 firms in 143 countries. The survey collects information on different firms' aspects such as performance, competition, labor, innovation, etc. (World Bank, 2019a, 2019b). We use the most updated data of each ASEAN country (*i.e.*, survey in 2015 for Indonesia, Malaysia, the Philippines, and Vietnam; survey in 2016 for Thailand). The questionnaires among countries are similar, which ensures data consistency. Furthermore, the study only concentrates on firms operating in the manufacturing industries.

After excluding outliers and missing observations, the final sample consists of 3,633 observations.

3.2 Research Method

The study investigates the possible impact of human capital on firm innovation by employing the following equation:

$$Innovation_i = \alpha_1 + \beta_1 Human\_capital_i + \beta_2 Control_i + \varepsilon_i \quad (1)$$

Innovation is the dependent variable revealing the degree of product innovation, which is coded "0" if the firm did not perform innovation. It is coded "1" if the firm carried out innovation activities, but the innovation is only new to the firm. It is coded "2" if the firm carried out new-to-the-market innovation activities. Thus, new-to-the-market innovation activities have the highest degree of radicalness.

Human capital refers to both general and specific human capital. General human capital is proxied by *Employee general education* and *Top manager's prior work experience*. Specific human capital is proxied by *Employee training*.

Control is the vector of control variables. We utilize four standard control variables in previous studies on firm innovation, comprising *Age*, *Size, Industry, Country* (Coad *et al*., 2016; González *et al.*, 2016; Hashi & Stojčić, 2013; Kasseeah, 2013). Table 1 presents details on the variables used in the analysis.

Table 1

Variable Description

	Description
Dependent variable	
Innovation	The level/radicalness of firm innovation, = 0 (no innovation), = 1 (innovation but only new the firm), = 2 (innovation and new to the market)
Independent variables (Human capital)	
Top manager's prior work experience	Top manager's years of experience in the current sector
Employee general education	Average years of education of a typical permanent full-time production employee
Employee training	Dummy variable, = 1 if the firm provided formal training for permanent full-time employees in the last complete fiscal year, = 0 otherwise
Control variables	
Age (log)	Firm's total years in operation (log)
Size (log)	Firm's total employees (log)
Industry	Two-digit dummy variable for the main registered operation industry of the firm
Country	Dummy variable for each country

Examining previous empirical literature on the role of human capital in firm innovation, we find that the research methods are diverse with the majority of studies using discrete choice modeling. Binary choice models are widely used, for example, probit model (Bauernschuster *et al.*, 2009; González *et al.*, 2016; McGuirk *et al.*, 2015), logit model (van Uden *et al.*, 2017). There is also an extension of the binary choice model to better deal with endogeneity such as instrumental variable (IV) probit model (Bauernschuster *et al*., 2009; Kato *et al*., 2015) and seemingly unrelated bivariate probit model (Bauernschuster *et al*., 2009). Additionally, to capture the degree of the dependent variable–innovation, ordinal response models are widely employed) (*e.g*., ordered probit model (Lund Vinding, 2006), ordered logit model (Protogerou *et al*., 2017)). Apart from discrete choice modeling, other types of regression are utilized such as OLS regression and 2SLS regression (Bauernschuster *et al*., 2009), hierarchical multiple regression (Marvel & Lumpkin, 2007), dynamic count data model (Gallié & Legros, 2012), count data model (González *et al*., 2016), Tobit model (Protogerou *et al*., 2017), Heckman's selection model (Fonseca *et al*., 2019).

In our study, the dependent variable has an ordinal characteristic. Therefore, an ordinal regression model is preferred to a binary choice model because an ordinal regression model (*i.e*., ordered logit model (OLM)) can consider the degree of innovation rather than just performing innovation or not in a binary choice model, which makes it possible to have more insights on the innovation performance.

According to Long and Freese (2014), an OLM is specified as follows:

$$Y_i^* = \mathrm{X}_i\beta + \varepsilon_i \tag{2}$$

where: Y_i^* is a latent variable. i is the firm. X_i is a set of covariates, and ε is the error term.

Equation (2) can be rewritten as models for binary outcomes with Y^* divided into j ordinal categories:

$$Y_i = m \text{ if } \tau_{m-1} \le Y_i^* \le \tau_m \text{ for } m = 1 \text{ to } j \tag{3}$$

Where the cutpoints from τ_1 to τ_{m-1} are estimated from the sample. The predicted probability is:

$$\Pr(Y = m|\mathrm{x}) = F(\tau_m - \mathrm{x}\beta) - F(\tau_{m-1} - \mathrm{x}\beta) \tag{4}$$

In equation (4), F represents the cumulative distribution function of ε. For an OLM, F is logistic. In Stata®, the OLM is estimated by the “ologit” command.

When estimating the OLM, the important “parallel regression/proportional odds” assumption (*i.e*., slope coefficients are unchanged over response categories) should be met (Long & Freese, 2014). However, this assumption is often violated in empirical studies because it is overly restrictive (Williams, 2006). Williams (2006) proposed a generalized ordered logit model (GOLM) that can deal with the limitation of this assumption. Following Williams (2006), the GOLM is written as follows:

$$P(Y_i > j) = g(X\beta) = \frac{\exp(\alpha_j + X_i\beta_j)}{1 + \{\exp(\alpha_j + X_i\beta_j)\}}, j = 1,2, \dots, m-1 \tag{5}$$

where: m represents the number of categories of the ordinal dependent variable. The probabilities that the dependent variable Y is in the categories $1, \dots, m$ are equal to:

$$\begin{gathered} P(Y_i = 1) = 1 - g(X_i\beta_j) \\ P(Y_i = j) = g(X_i\beta_{j-1}) - g(X_i\beta_j) \quad j = 2, \dots, m-1 \\ P(Y_i = m) = g(X_i\beta_{m-1}) \end{gathered} \tag{6}$$

In our analysis, $m = 3$, we have the following comparison groups for the three categories. For $j = 1$, category 1 is contrast to categories 2 and 3; for $j = 2$, categories 1 and 2 are contrast to category 3.

GOLM is more advantageous than the OLM in working with the "parallel regression/proportional odds" assumption by "fitting partial proportional odds models, where the parallellines constraint is relaxed only for those variables where it is not justified" (Williams, 2006, p. 64). In particular, different from the OLM ($\beta's$ are the same for all values of j), in the GOLM one or more $\beta's$ differ across values of j. In Stata®, the GOLM is estimated by "gologit2" procedure developed by Williams (2006).

Another issue is the hierarchical structure of our dataset. Observations are clustered in three-level hierarchies: firms (level 1) nested within industries (23 industries) (level 2) within countries (5 countries) (level 3). The popular assumption of traditional regression models is that observations are independent of each other, which is plausible with data randomly collected from a vast population. Nevertheless, due to the hierarchical nature of the dataset, observations from the same group/cluster (*i.e.*, industry/country) may relate to each other. With clustered/nested data, traditional regression models will give incorrect standard errors that affect the estimation results (McCoach, 2019). Due to this shortcoming, multilevel mixed-effects models are considered superior when working with hierarchical data. Hence, a multilevel mixed-effects ordered logit model (MOLM), an extension of the OLM to take into account hierarchical data, will be utilized in the analysis (StataCorp, 2017). A MOLM is specified as follows:

$$Y_{ijk}^{*} = \mathrm{X}_{ijk}\beta + u_k + v_{ij} + \varepsilon_{ijk} \tag{7}$$

where: Y_{ijk}^{*} is a latent variable representing firm i, industry j, and country k. ε_{ijk} is a set of firm-level random effects (both random intercepts and coefficients). ε_{ijk} is distributed as logistic with mean 0 and variance $\pi^2/3$. v_{ij} is a set of industry-level random intercept and coefficients. u_k is a set of country-level random intercept and coefficients.

If m represents the number of categories of the ordinal dependent variable, the ordered observed outcomes (Y_{ijk}^{*}) can be calculated as follows:

$$Y_{ijk}^{*} = \begin{cases} 1 \ \text{if}\, Y_{ijk}^{*} \leq \mu_1 \\ 2 \ \text{if}\, \mu_1 < Y_{ijk}^{*} \leq \mu_2 \\ \dots \\ \dots \\ \dots \\ m \ \text{if}\, \mu_{m-1} < Y_{ijk}^{*} \end{cases} \tag{8}$$

where: μ_1, μ_2, and μ_{m-1} are cutoff points or thresholds.

Equation 7 can be rewritten as:

$$\mathrm{logit}(p_{ijk}) = \log\left[\frac{p_{ijk}}{(1-p_{ijk})}\right] = \mathrm{X}_{ijk}\beta + u_k + v_{ij} + \varepsilon_{ijk} \tag{9}$$

where: $p_{ijk} = \Pr(Y_{ijk} = m)$

From Equation 9, the probability of observing firm outcome m can be derived as:

$$\begin{aligned} \Pr\left(Y_{ijk} = m \middle| \mu, u_k, v_{ij}\right) &= \Pr(\mu_{m-1} < \mathrm{X}_{ijk}\beta + u_k + v_{ij} + \varepsilon_{ijk} \leq \mu_m) \\ &= F(\mu_m - \mathrm{X}_{ijk}\beta - u_k - v_{ij}) - F(\mu_{m-1} - \mathrm{X}_{ijk}\beta - u_k - v_{ij}) \end{aligned} \tag{10}$$

A likelihood-ratio test is used to compare the MOLM with the standard OLM. Significant results indicate that the MOLM is more favorable than the standard OLM. In Stata®, the MOLM is estimated by the "meologit" command.

Therefore, to address the "parallel regression/proportional odds" assumption and hierarchical structure, this study utilizes both the GOLM and MOLM along with the OLM (for comparison). Following this strategy, we can address the two most popular problems of ordinal regression models, which are not fully dealt with in previous studies on this research theme using discrete choice modeling.

4. Findings and Discussion

4.1 Descriptive Statistics

Table 2 shows the radicalness of innovation by country. Among the five economies, Vietnam and the Philippines have the highest rate of innovation (approximately 35% of firms carried out innovation). In contrast, Thailand has the lowest innovation rate with only more than 8% of firms engaging in innovation activities.

Table 2

Innovation by Country

	No innovation	"New-to-the-firm" innovation	"New-to-the-market" innovation	Total
Indonesia	885	27	96	1,008
Row %	87.8	2.68	9.52	100
Malaysia	403	21	39	463
Row %	87.04	4.54	8.42	100
Philippines	593	129	188	910
Row %	65.16	14.18	20.66	100
Thailand	603	7	48	658
Row %	91.64	1.06	7.29	100
Vietnam	389	70	135	594
Row %	65.49	11.78	22.73	100
Total	2,873	254	506	3,633
Row %	79.08	6.99	13.93	100

Table 3 presents the radicalness of innovation by firm size. Micro firms have the lowest rate of innovation activities. In particular, only about 10% of micro firms performed innovation, and approximately 6% of micro firms conducted innovation new to the market. In contrast, large firms are the most innovative ones with more than 31% of large firms executing innovation activities. Furthermore, large firms also scored the best in terms of radicalness with nearly 21% of large firms reporting innovation that is new to the market.

Table 3

Innovation by Firm Size

	No innovation	"New-to-the-firm" innovation	"New-to-the-market" innovation	Total
Micro	354	17	23	394
Row %	89.85	4.31	5.84	100
Small	1,150	93	162	1,405
Row %	81.85	6.62	11.53	100
Medium	997	100	194	1,291
Row %	77.23	7.75	15.03	100

	No innovation	"New-to-the-firm" innovation	"New-to-the-market" innovation	Total
Large	372	44	127	543
Row %	68.51	8.1	23.39	100
Total	2,873	254	506	3,633
Row %	79.08	6.99	13.93	100

Note: Following the conventional classification of firm size, firms are categorized into four groups: micro: < 10 employees, small: 10-49 employees, medium: 50-249 employees, large: 250 employees or more (OECD, 2018).

Table 4 shows the cross-tabulation of firms by innovation and employee training status. While only 28% of non-innovative firms provided formal training for employees, nearly half of innovative ones (both types of innovation) performed such activity. This may suggest that employee training is positively related to better innovation outcomes.

Table 4

Innovation by Employee Training Status

Innovation	Employee training		
	No	Yes	Total
No innovation	2,048	814	2,862
Row %	71.56	28.44	100
"New-to-the-firm" innovation	137	116	253
Row %	54.15	45.85	100
"New-to-the-market" innovation	266	239	505
Row %	52.67	47.33	100
Total	2,451	1,169	3,620
Row %	67.71	32.29	100

Table 5 shows the cross-tabulation of firms by innovation status and the mean of top manager's prior work experience and employee general education in each respective innovation type. The same pattern in Table 4 emerges. Specifically, the average years of top manager's prior work experience and employee general education of innovative firms are higher than non-innovative ones. Thus, it may suggest that higher experience of top managers and more educated employees are positively associated with innovation performance.

Table 5

Innovation by Top Manager's Prior Work Experience and Employee General Education

Innovation	Top manager's prior work experience (mean of years)	Employee general education (mean of years)
No innovation	17.68	10.20
"New-to-the-firm" innovation	20.53	10.61
"New-to-the-market" innovation	19.86	10.62

Table 6 presents the summary statistics. On average, a top manager has over 18 years of working in the current sector. A typical employee has an average of 10 years of schooling. Furthermore, 32% of firms organized formal employee training. The average year in the business operation of a firm is over 19 years, and the average number of a firm's employees is approximately 187 employees.

Table 6

Summary Statistics

	Number of observations	Mean	Std. Dev.	Min.	Max.
Innovation	3,633	0.348	0.711	0	2
Top manager's prior work experience	3,460	18.187	10.225	2	70
Employee general education	3,633	10.284	2.684	0	20
Employee training	3,620	0.323	0.468	0	1
Age	3,633	19.579	11.416	1	80
Age (log)	3,633	2.800	0.623	0	4.382
Size	3,633	187.529	688.284	2	20000
Size (log)	3,633	3.985	1.444	0.693	9.903

Table 7 shows the pairwise correlation coefficients of independent and control variables. All the correlation values are below 0.5, which implies that a strong correlation between variables does not exist. So, there is no evidence of the possible multicollinearity problem (Dormann *et al*., 2013).

Table 7

Pairwise Correlations

	Top manager's prior work experience	Employee general education	Employee training	Age (log)	Size (log)
Top manager's prior work experience	1				
Employee general education	0.0051	1			
Employee training	0.0582***	0.0671***	1		
Age (log)	0.4065***	-0.0306*	0.1251***	1	
Size (log)	0.0335**	0.1232***	0.3445***	0.2092***	1

*Note: *, **, and *** indicate significance at 10%, 5% and 1% levels, respectively.*

4.2 Results

Table 8 shows the estimation results. The likelihood-ratio statistic in the MOLM is highly significant, implying that hierarchical structure is a problem, and the MOLM is more effective in estimating our specific dataset. Furthermore, the "Brant test" of the "parallel regression/proportional odds" assumption shows evidence that this assumption has been violated (not shown here for brevity). Hence, the MOLM and GOLM are more preferred than the standard OLM. However, it important to note that all three models show similar results, which increases the results' robustness.

Three major findings regarding the role of human capital in firm innovation emerge. First, top manager's prior work experience in the current sector has a significantly positive impact on the radicalness of product innovation in all three models. Hence, hypothesis 1 is strongly supported in the ASEAN context. The result lends support to the arguments in previous studies that as top managers have more time working in the current industrial sector, they are likely to accumulate more understanding of state-of-the-art technologies, customer preferences, competition in the market as well as relationships with innovation-related organizations *(i.e.*, universities, research institutes), which helps enhance innovation performance (Kato *et al*., 2015; Marvel & Lumpkin, 2007; Protogerou *et al*., 2017). This finding is also in line with our observation shown in Table 5 that top managers of innovative firms have more experience in the current sector than non-innovative ones (*i.e.*, 20.53 years of "new-to-the-firm" and 19.86 years of "new-to-the-market" firms in comparison with 17.68 years of non-innovative ones).

Second, the coefficients of *Employee general education* are highly significant and positive in all three models, indicating that the formal educational level of employees is positively related to the propensity to innovate more radically. This delivers support for Hypothesis 2. The result supports prior research that formal education enables employees to acquire sophisticated, specialized knowledge and utilize technological progress for innovative activities (Fonseca *et al*., 2019; Lund Vinding, 2006; McGuirk *et al*., 2015; Protogerou *et al*., 2017). This is especially relevant in a context where technologies and customers' preferences change rapidly like ASEAN as one of the world's most dynamic regions in terms of trade and business, and ASEAN is integrating deeply into the world's economy (The ASEAN Secretariat, 2019). Therefore, to sustain competitiveness, firms have to enhance their technologies and innovation capacities (OECD, 2013), and the educational level of employees, especially those involved in R&D, plays an important role here. As Table 5 shows, in our research sample, the innovative firms have higher average years of employee general education than the non-innovative ones (i.e., 10.62 years of "new-to-the-market" innovative firms versus 10.20 years of non-innovative ones).

Table 8

Estimation Results

	GOLM		MOLM	OLM
	Non-innovative firms versus firms with "new-to-the-firm" or "new-to-the-market" innovation	Non-innovative firms or firms with "new-to-the-firm" innovation versus firms with "new-to-the-market" innovation		
Top manager's prior work experience	0.015***	0.009*	0.013***	0.013***
	(0.005)	(0.005)	(0.005)	(0.005)
Employee general education	0.074***	0.074***	0.066***	0.072***
	(0.020)	(0.020)	(0.020)	(0.020)
Employee training	0.395***	0.395***	0.372***	0.390***
	(0.103)	(0.103)	(0.103)	(0.103)
Age (log)	0.233***	0.233***	0.228***	0.235***
	(0.085)	(0.085)	(0.085)	(0.085)
Size (log)	0.182***	0.182***	0.188***	0.181***
	(0.033)	(0.033)	(0.033)	(0.033)
Industry (dummies)	Yes	Yes	Yes	Yes

	GOLM		MOLM	OLM
	Non-innovative firms versus firms with “new-to-the-firm” or “new-to-the-market” innovation	Non-innovative firms or firms with “new-to-the-firm” innovation versus firms with “new-to-the-market” innovation		
Country (dummies)	Yes	Yes	Yes	Yes
Constant	-3.509***	-4.012***		
	(0.851)	(0.854)		
/cut1			3.995	3.500
			(0.468)	(0.847)
/cut2			4.539	4.044
			(0.470)	(0.848)
Country (var(_cons))			0.590	
			(0.386)	
Country > Industry (var(_cons))			0.049	
			(0.032)	
			LR test versus ologit model: $\chi2$ = 253.33	
			Prob >= $\chi2$ = 0.0000	
LR $\chi2$	520.48			449.01
Wald $\chi2$			122.79	
Prob > $\chi2$	0.000		0.000	0.000
Number of observations	3,452		3,452	3,452

*Note: Standard errors are in parentheses. *, **, and *** indicate significance at 10%, 5% and 1% levels, respectively.*

Third, the coefficients of *Employee training* are highly significant and positive in all three models, suggesting that employee training contributes positively to firm innovation. Thus, Hypothesis 3 is also strongly supported. The result supports previous arguments that formal training helps employees increase their knowledge and skills to absorb complicated technological knowledge and progress, which supports firms to move closer to the technological frontier and hence have better innovation performance, especially radical innovation (Bauernschuster *et al.*, 2009; McGuirk *et al.*, 2015; van Uden *et al.*, 2017). This finding is in line with our observation shown in Table 4 that the employee training strategy is employed by innovative firms much than non-innovative ones (*i.e.*, approximately 46% and 47% of “new-to-the-firm” and “new-to-the-market” firms compared to 28% of non-innovative ones). More specifically, Table 9 shows that except Malaysia, the other four ASEAN countries witnessed the strong emphasis of innovative firms on employee training than non-innovative ones. The *Global Competitiveness Report 2018* shows that the “Quality of vocational training” rankings (rank/140 economies) of ASEAN countries are generally low.

More specifically, except Malaysia (9), other countries have low rankings (*i.e.*, Indonesia (34), Philippines (26), Thailand (75), Vietnam (115)) (Schwab, 2018) (the year 2018 is the earliest year when WEF reported data for this indicator). The low employee training rate of innovative firms in Malaysia may be partially due to the relatively high quality of vocational training; thus, formal employee training may not very important for firm innovation in Malaysia. In other countries, especially Vietnam, due to the medium and low quality of vocational training, innovative firms tended to perform formal employee training to update employees with modern skills and technological knowledge, which is important for innovation efforts. The data from the *Global Competitiveness Report 2019* also show a similar pattern for the "Quality of vocational training" indicator (*i.e.*, rank/141 economies, Malaysia (12), Indonesia (37), Philippines (29), Thailand (74), Vietnam (102)) (Schwab, 2019).

Table 9

Innovation by Employee Training Status and Country

Innovation	Indonesia		Malaysia		Philippines		Thailand		Vietnam	
	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
No innovation	90.50	9.50	63.59	36.41	51.61	48.39	61.06	38.94	83.20	16.80
"New-to-the-firm" innovation	85.19	14.81	80.95	19.05	40.63	59.38	42.86	57.14	60.00	40.00
"New-to-the-market" innovation	76.04	23.96	79.49	20.51	29.41	70.59	52.08	47.92	60.74	39.26

Note: The number is in percentage (%).

Regarding the age of the firm, older firms are more likely to innovate than younger ones. The possible explanation is that older firms may have the advantages coming from the accumulated resources, capabilities, and experience that enable them to have better innovation performance. Furthermore, when firms are in business longer, they tend to have a better reputation, market position, and relationships, which facilitates new product or service development.

The size of the firm is also positively related to the likelihood of innovation performance. The possible explanation is that bigger firms tend to have abundant resources (*i.e.*, personnel, capital) for performing innovation compared to smaller ones.

4.3 Robustness Test

Long and Freese (2014, p. 310) suggested that "you always compare the results from ordinal models with those from a model that does not assume ordinality", so we employ a multinomial logit model (MLM) to test the robustness of the main results when the ordinal characteristic is not considered. Table 10 reports the estimation results. The coefficients of *Top manager's prior work experience*, *Employee general education*, and *Employee training* remain positive and significant, supporting Hypotheses 1, 2, and 3 respectively. Thus, the robustness test results confirm the main results in Table 8.

Table 10

Robustness test

	MLM	
	“new-to-the-firm” innovation versus no innovation	“new-to-the-market” innovation versus no innovation
Top manager’s prior work experience	0.021***	0.010*
	(0.007)	(0.006)
Employee general education	0.101***	0.067***
	(0.036)	(0.024)
Employee training	0.290*	0.442***
	(0.163)	(0.121)
Age (log)	0.114	0.289***
	(0.134)	(0.101)
Size (log)	0.099*	0.204***
	(0.054)	(0.039)
Industry (dummies)	Yes	Yes
Country (dummies)	Yes	Yes
Constant	-17.416	-3.825***
	(1004.310)	(0.863)
LR chi2	538.37	
Prob > chi2	0.000	
Number of observations	3,452	

*Note: Standard errors are in parentheses. *, **, and *** indicate significance at 10%, 5% and 1% levels, respectively. The base outcome is “no innovation”.*

5. Conclusions and Implications

Employing three different ordinal logistic regression models (GOLM, MOLM, and OLM), the study explores the role of human capital in firm innovation. The findings show evidence confirming that both general human capital and specific human capital are positively related to the likelihood of more radical innovation. The results are robust to various robustness tests.

Given the empirical results, the study proposes two important implications. First, firms should channel more resources into training, especially formal training for employees so that the labor force can update intensive knowledge about technologies, which can be applied to improving existing products or processes. The formal training should not be too generic; instead, it should target two most important set of skills proposed by (OECD, 2011): (i) “digital-age literacy” skills that allow employees to access, absorb, and create based on giant information in the current knowledge economy, (ii) “technical skills” that builds employees’ competencies for improving products and services. Second, at the macro level, governments should channel more resources into education, which helps boost innovation. One of the breakthroughs should be the investment in digital technology in education to facilitate innovative pedagogic models and enhance E-learning and access to open educational resources. As a result, the teaching and learning practices are transformed into new horizons towards a more creative workforce.

References

Acemoglu, D., 1997. Training and innovation in an imperfect labour market. *The Review of Economic Studies,* 64, pp.445-464.

Barney, J.B., 1991. Firm Resources and Sustained Competitive Advantage. *Journal of Management,* 17, pp.99-120.

Bauernschuster, S., Falck, O. and Heblich, S., 2009. Training and innovation. *Journal of Human Capital,* 3, pp.323-353.

Becker, G.S., 1964. *Human Capital: A Theoretical and Empirical Analysis with Special Reference to Education.* Chicago: The University of Chicago Press.

Blundell, R., Dearden, L., Meghir, C. and Sianesi, B., 1999. Human capital investment: the returns from education and training to the individual, the firm and the economy. *Fiscal studies,* 20, pp.1-23.

Coad, A., Segarra, A. and Teruel, M., 2016. Innovation and firm growth: Does firm age play a role? *Research Policy,* 45, pp.387-400.

Cohen, W.M. and Levinthal, D.A., 1990. Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly,* 35, pp.128-152.

Dormann, C.F., Elith, J., Bacher, S., Buchmann, C., Carl, G., Carré, G., Marquéz, J.R.G., Gruber, B., Lafourcade, B. and Leitão, P.J., 2013. Collinearity: a review of methods to deal with it and a simulation study evaluating their performance. *Ecography,* 36, pp.27-46.

Edwards-Schachter, M., 2018. The nature and variety of innovation. *International Journal of Innovation Studies,* 2, pp.65-79.

ERIA, 2018. *Innovation Policy in ASEAN*. Jakarta: Economic Research Institute for ASEAN and East Asia. Available at: <https://www.eria.org/uploads/media/Innovation_Policy_in_ASEAN.pdf> [Accessed 10 November 2019].

Fagerberg, J., Fosaas, M. and Sapprasert, K., 2012. Innovation: Exploring the knowledge base. *Research policy,* 41, pp.1132-1153.

Fonseca, T., De Faria, P. and Lima, F., 2019. Human capital and innovation: the importance of the optimal organizational task structure. *Research Policy,* 48, pp.616-627.

Gallié, E.-P. and Legros, D., 2012. Firms' human capital, R&D and innovation: a study on French firms. *Empirical Economics,* 43, pp.581-596.

Gault, F., 2018. Defining and measuring innovation in all sectors of the economy. *Research Policy,* 47, pp.617-622.

González, X., Miles-Touya, D. and Pazó, C., 2016. R&D, worker training and innovation: firm-level evidence. *Industry and Innovation,* 23, pp.694-712.

Hashi, I. and Stojčić, N., 2013. The impact of innovation activities on firm performance using a multi-stage model: Evidence from the Community Innovation Survey 4. *Research Policy,* 42, pp.353-366.

IMF, 2018. World Economic Outlook Database. [online] Available at: <https://www.imf.org/en/Publications/SPROLLs/world-economic-outlook-databases> [Accessed 08 October 2019].

Jiménez-Jiménez, D. and Sanz-Valle, R., 2011. Innovation, organizational learning, and performance. *Journal of business research,* 64, pp.408-417.

Kasseeah, H., 2013. Innovation and performance in small-and medium-sized enterprises: evidence from Mauritius. *Innovation and Development,* 3, pp.259-275.

Kato, M., Okamuro, H. and Honjo, Y., 2015. Does Founders' Human Capital Matter for Innovation? Evidence from Japanese Start-ups. *Journal of Small Business Management,* 53, pp.114-128.

Long, J.S. and Freese, J., 2014. *Regression Models for Categorical Dependent Variables Using Stata,* 3 ed.

Lund Vinding, A., 2006. Absorptive capacity and innovative performance: A human capital approach. *Economics of Innovation and New Technology,* 15, pp.507-517.

Lundvall, B.-Ä. and Johnson, B., 1994. The learning economy. *Journal of Industry Studies,* 1, pp.23-42.

Ma, L., Zhai, X., Zhong, W. and Zhang, Z.-X., 2019. Deploying human capital for innovation: A study of multi-country manufacturing firms. *International Journal of Production Economics,* 208, pp.241-253.

Marvel, M.R. and Lumpkin, G.T., 2007. Technology entrepreneurs' human capital and its effects on innovation radicalness. *Entrepreneurship Theory and Practice,* 31, pp.807-828.

Mccoach, D.B., 2019. Multilevel Modeling. *In* G.R. Hancock, Stapleton, L. M., Mueller, R. O. (ed.) *The reviewer's guide to quantitative methods in the social sciences* 2ed. NY: Routledge, pp.292-312.

Mcguirk, H., Lenihan, H. and Hart, M., 2015. Measuring the impact of innovative human capital on small firms' propensity to innovate. *Research Policy,* 44, pp.965-976.

Mincer, J., 1962. On-the-job training: Costs, returns, and some implications. *Journal of Political Economy,* 70, pp.50-79.

Moagăr-Poladian, S., Folea, V. and Păunică, M., 2017. Competitiveness of EU member states in attracting EU funding for research and innovation. *Romanian Journal of Economic Forecasting,* 20(2), pp.150-167.

Murovec, N. and Prodan, I., 2009. Absorptive capacity, its determinants, and influence on innovation output: Cross-cultural validation of the structural model. *Technovation,* 29, pp.859-872.

OECD, 2001. *The Well-being of Nations: The Role of Human and Social Capital*. Paris: OECD. Available at: <https://www.oecd-ilibrary.org/education/the-well-being-of-nations_9789264189515-en> [Accessed 15 August 2019].

OECD, 2005. *The measurement of scientific and technological activities Oslo Manual Guidelines for collecting and interpreting innovation data,* 3 ed. Paris: OECD Eurostat. Available at: <https://www.oecd-ilibrary.org/science-and-technology/oslo-manual_9789264013100-en> [Accessed 25 August 2019].

OECD, 2010. *Ministerial Report on the OECD Innovation Strategy Innovation to strengthen growth and address global and social challenges Key Findings*. Paris: OECD. Available at: <https://www.oecd.org/sti/45326349.pdf> [Accessed 18 September 2019].

OECD, 2011. *Skills for innovation and research*. Paris: OECD. Available at: <https://www.oecd-ilibrary.org/science-and-technology/skills-for-innovation-and-research_9789264097490-en> [Accessed 25 September 2019].

OECD, 2013. *OECD Reviews of Innovation Policy Innovation in Southeast Asia*. Paris: OECD Publishing. Available at: <https://www.oecd.org/sti/inno/innovation-in-southeast-asia-2012-9789264128712-en.htm> [Accessed 12 September 2019].

OECD, 2018. *Enterprises by business size.* [online] Available at: <https://data.oecd.org/entrepreneur/enterprises-by-business-size.htm> [Accessed 12 October 2019].

Pelinescu, E., Pauna, C., Saman, C. and Diaconescu, T., 2019. Human capital, innovation and economic growth in the EU countries. *Romanian Journal of Economic Forecasting,* 22(4), pp.160-173.
Protogerou, A., Caloghirou, Y. and Vonortas, N.S., 2017. Determinants of young firms' innovative performance: Empirical evidence from Europe. *Research Policy,* 46, pp.1312-1326.
Rodil, Ó., Vence, X. and Del Carmen Sánchez, M., 2016. The relationship between innovation and export behaviour: The case of Galician firms. *Technological Forecasting and Social Change,* 113, pp.248-265.
Santi, C. and Santoleri, P., 2017. Exploring the link between innovation and growth in Chilean firms. *Small Business Economics,* 49, pp.445-467.
Schumpeter, J.A., 1934. *The theory of economic development: an inquiry into profits, capital, credit, interest, and the business cycle.* MA: Harvard University Press.
Schwab, K., 2018. *The global competitiveness report 2018.* Geneva: World Economic Forum. Available at: <http://www3.weforum.org/docs/GCR2018/05FullReport/TheGlobalCompetitivenessReport2018.pdf> [Accessed 22 November 2019].
Schwab, K., 2019. *The global competitiveness report 2019.* Geneva: World Economic Forum. Available at: <http://www3.weforum.org/docs/WEF_TheGlobalCompetitivenessReport2019.pdf> [Accessed 20 November 2019].
Shane, S., 2000. Prior knowledge and the discovery of entrepreneurial opportunities. *Organization Science,* 11, pp.448-469.
Statacorp, L.P., 2017. *Stata multilevel mixed-effects reference manual release 15*. TX: Stata Press.
Sun, X., Li, H. and Ghosal, V., 2020. Firm-level human capital and innovation: Evidence from China. *China Economic Review,* 59, 101388.
The Asean Secretariat, 2019. *ASEAN Integration Report 2019*. Jakarta: ASEAN Secretariat. Available at: <https://asean.org/wp-content/uploads/2019/11/ASEAN-integration-report-2019.pdf> [Accessed 20 December 2019].
Tidd, J. and Bessant, J.R., 2009. *Managing innovation: integrating technological, market and organizational change,* 4 ed. John Wiley & Sons.
Unger, J.M., Rauch, A., Frese, M. and Rosenbusch, N., 2011. Human capital and entrepreneurial success: A meta-analytical review. *Journal of business venturing,* 26, pp.341-358.
Van Uden, A., Knoben, J. and Vermeulen, P., 2017. Human capital and innovation in Sub-Saharan countries: a firm-level study. *Innovation,* 19, pp.103-124.
Williams, R., 2006. Generalized ordered logit/partial proportional odds models for ordinal dependent variables. *Stata Journal,* 6, pp.58-82.
World Bank, 2019a. About Us. [online] Available at: <https://www.enterprisesurveys.org/about-us> [Accessed 11 November 2019].
World Bank, 2019b. Survey Methodology. [online] Available at: <https://www.enterprisesurveys.org/methodology> [Accessed 11 November 2019].
Ziemnowicz, C., 2013. Joseph A. Schumpeter and innovation. *Encyclopedia of Creativity, Invention, Innovation and Entrepreneurship*, pp.1171-1176.