The Effects of Technological Innovations on Competitiveness and Economic Growth

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THE EFFECTS OF TECHNOLOGICAL INNOVATIONS ON OMPETITIVENESS AND ECONOMIC GROWTH

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PREFACE

In the world economy, all economic players have to analyse the changing dynamics of sharpening global competition and transform their systems-structures to keep up with these competitive conditions. In order to steer the global competitive dynamics, they have to develop strong innovations with high added value that differentiate them from their competitors.

In the world ecosystem, where the global competitive climate is extremely destructive, companies and countries should correctly analyse the dynamics of global competition, their resources, strengths and weaknesses, opportunities and threats from the external environment. On the other hand, they have to formulate their own goals and global competition strategies, through which they can achieve these goals most effectively.

Firms and countries should establish an effective corporate governance-production architecture in order to sustain their competitive edge, profitability and growth at the global level in the long term. On the other hand, they should be able to offer high value added goods and services to the market in more advantageous conditions compared to their competitors, considering other criteria such as price, cost, efficiency, efficiency, quality, aesthetics and image.

As a result, a high level Science-R&D-technology-innovation management-production architecture is of great importance for a successful global competition strategy at the microeconomic and macroeconomic levels.

In this context, in this study, we focused on the effects of the Science-R&D-technology-innovations on the global competition dynamics and sustainable economic growth at the microeconomic and macroeconomic levels for different countries and regions in the world economy.

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Editors
Ercan Sarıdoğan
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CHAPTER 1

EXPLAINING FACTORS OF INNOVATION FOR TURKISH SMEs: A FIRM-LEVEL EMPIRICAL ANALYSIS

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Abstract

Small and medium sized enterprises (SMEs) account for a considerable proportion of economic development and job creation, making their survival and growth crucial, especially for developing countries. As innovation is one of the vital sources of prosperity for those establishments, it would be extremely helpful to identify the factors that promote or hinder it. Analyzing the World Bank's Regional Enterprise Survey, this paper investigates the determinants of innovation activities of Turkish SMEs and aims to contribute to the knowledge on those businesses in the context of a developing country. Our analyses show that the main factors that affect SMEs being innovative in Turkey are their size, ownership type, experience in the international market, obtaining government grants, existence of women in the ownership and the governance environment, and – in particular - corruption and labor regulations.

Keywords: Small and medium sized enterprises (SMEs), Innovation, Job Creation, Turkish Economy.

JEL Classifications*:* L21, L26, L53, M21, O30.

1. Introduction

A substantial portion of the private sector is dominated by small and medium sized enterprises (SMEs; hereafter) in most developed and developing countries and they unsurprisingly account for a substantial proportion of economic activity (World Bank, 2004; Akman and Cengiz, 2008). The contribution of SMEs to the economic development of countries is well addressed in the literature. Beck et al. (2005), for example, demonstrated through an analysis of data from 54 countries mainly including developed economies, that GDP per capita and contribution of SMEs are positively correlated. Ayyagari et al. (2004), analyzing data from 104 developing countries also found that SMEs are significant providers of employment, suggesting that this is mostly the case for low income countries rather than those that are middle or high-income. Schumpeter (1954) found that both innovation and entrepreneurship are key sources of economic prosperity. Therefore, one can claim that the level of economic development is highly dependent on the success of SMEs both in developed and developing countries.

Although the flexibility of SMEs allows them to be in an advantageous position compared to larger firms because rapid developments in technology and production processes benefit SMEs more as a result of their higher ability to adapt to unexpected and unsteady circumstances in both local and global level (Irfanoglu et al., 2008), they still need to be innovative in order to maintain competitiveness and achieve long-term presence in an ever changing business environment (Petrovska, 2015). In the context of small manufacturing firms, for example, Freel (2000) asserted that innovation is one of the most critical elements for economic development and it is also critical for firms' competition. Nevertheless, innovation needs to tackle particular barriers that are inherent in change (Madrid-Guijarro et al., 2009). For instance, Aydin et al. (2014) argues that there should be financial incentives or policy initiatives in order to ensure that Turkish SMEs are competitive and are able to overcome various barriers.

The classification of SMEs in Turkey, is shown in Table 1 below. The definition of SMEs could differ for international organizations and countries, but they are generally identified according to the total number of employees they have (Aydin et al., 2014).

Table 1. Definition of SMEs in Turkey.

Scale	Total number of employees	Annual turnover (million TL)	Annual Balance Sheet (million TL)
Micro	1-9	0 < and ≤ 1	0 < and ≤ 1
Small	10-49	1 < and ≤ 8	1 < and ≤ 8
Medium	50-249	8 < and ≤ 40	8 < and ≤ 40

Source: Turkish Official Gazette (2012).

SMEs constitute a crucial segment of the Turkish economy. According to Turkish Statistical Institute statistics (2016), 99.8% of all enterprises in Turkey are classified as SMEs, and they provide a considerable 73.5% of total employment, as well as accounting for 55.1% of the nation's total exports. However, research conducted by the Turkish Bureau of Labor and Statistics (2012) demonstrated that SMEs involved in production and/or process innovation made up only 27% of all SMEs in a three-year period. Moreover, it seems that those SMEs involved in innovative activities are mainly working with low technology as can be observed in Table 2 below. This use of low level technology by SMEs is also not in line with the policy target of Turkey's SME Development Organization (2018) as stated in their report "A Strategy and Action Plan for SMEs" which states that they aim to increase the international competitiveness of Turkish SMEs.

Table 2. Share of SMEs in manufacturing sector according to their level of technology and size, 2014 (%).

	Technology Level			
Size	**High-tech**	**Medium-high tech**	**Medium-low tech**	**Low-tech**
1-19	0.2	8.3	30.9	59.6
20-49	0.9	17.6	28.4	53.0
50-249	1.5	17.4	31.4	49.7
SMEs (1-249)	0.3	9.1	31.0	59.7

Source: Turkish Statistical Institute, small and medium size enterprise statistics (2016).
Notes: The classifications here do not consider the annual turnover or balance sheet. Rather, it focuses on the size of SMEs.

Thus, although the role of SMEs and their innovative behavior for the Turkish economy is not negligible, the level of technology they use is at very low levels which makes it important to understand the reasons why. Explaining those factors that obstruct their innovativeness will not only improve competitiveness and economic advantage of SMEs but also help the Turkish economy and improve the efficiency of the Turkish labor force.

Since there is a limited amount of research on the innovative behavior of Turkish SMEs, this study aims to contribute to the understanding of factors behind the innovation activities of SMEs in Turkey and to provide policy suggestions. We believe that this is an important objective, as explaining obstacles to innovation can support SMEs to stimulate development of a business and economic environment that encourages them to work with high levels of technology (Hadjimanolis, 1999).

The remaining parts of the paper are organized as follows: the following section introduces previous research on innovative behavior of SMEs which helps us determine our hypotheses to be tested. The next section then explains the data used in the paper, which is followed by a description of the methodology employed in the empirical analysis. Afterwards the empirical findings are presented and final section concludes the paper.

2. Innovative Behavior of SMEs

Having realized their prominent position in terms of economic growth and employment, most governments of countries in both the developing and developed world have already subscribed to the goal of encouraging innovation activities of SMEs (Keizer et al., 2002). Innovation has been encouraged, because it is well known that it is a crucial component for SMEs' survival and future development (Acs et al., 1990). The vulnerability of those firms is that they are relatively small in a rapidly globalizing business environment – this could be balanced out with a higher ability of innovation (Hoffman et al. 1998). McAdam and McConvery (2004) stated that businesses that take innovation seriously perform better than those that remain old fashioned.

Before providing further details concerning the current literature, the notion of 'innovation' needs to be distinguished from 'invention' due to a widespread misunderstanding within society (Fagerberg et al. 2004). Invention is an idea which may or may not produce economic benefit, whereas innovation is an execution of a new idea or a new application to the current idea or product, or a new and improved process for producing an existing product (Schumpeter, 1934). In this paper, what we mean by innovation is in line with Oslo Manual's definition:

> *'... as the implementation of a new or significantly improved product (good or service), or process, a new marketing method, or a new organisational method in business practices, workplace organisation or external relations.' (OECD/Eurostat, 2005 p.46)*

Following the definition of innovation, firms can make their investments in intellectual capital or innovation inputs, which could be tangible (equipment, facilities etc.) or intangible (human capital, being creative etc.), in order to have an innovative output. (Cirera et al., 2016) Given that, Roper (1997) and Freel (2005) showed higher levels of innovative capacity are associated with better performance for SMEs in the UK and Ireland.

Economists prefer to infer results from industry or economy-wide levels of employment for the benefit of society but it should be noted that firm-level data is the actual source for the level of employment in each sector (Harrison, 2014). Thus, in this context, the Oslo Manual divided innovation into three categories by separating firm-level, world-level and market-level innovation (OECD, 2015). In general, the literature has concentrated on worldwide and market innovations whereas firm level innovations are underrated, especially when the subject is SMEs (Martínez-Román et al., 2017).

Empirical research revealed that product innovation positively affects job creation whereas numerous theoretical studies point out that innovation as a potential risk for higher unemployment due to its role in substituting labor by capital (Pianta, 2006; Hall et al,. 2008). To illustrate this point, according to Castillo (2014), both process and product innovation created more and better jobs for SMEs in terms of real wages in Argentina and the reason behind this improvement was essentially the Support Program for Organizational Change which led to these innovative activities.

Unfortunately, SMEs may experience impediments which are more challenging than their larger competitors in terms of generating innovation due to a lack of adequate resources (Griffith et al., 2009; Nieto and Santamaria, 2009). Barriers to innovation could be in the form of external obstacles and internal difficulties resulting from owner-manager involvement (Piatier, 1984.) The majority of studies focus on internal difficulties which affects the success or failure of innovation (Hoffman et al., 1998). However, external factors that affect SMEs' innovativeness have been understudied, especially in emerging economies (Zhu et al., 2011).

2.1. Governance Environment

External circumstances both affect and restrict the innovative capacity of SMEs and harm owner-managers in the matter of their competitive plans against larger firms (Demirbas et al., 2011). External barriers include excessive bureaucracy (Hadjimanolis, 1999), a poor climate for doing business such as a corrupted, unfair court system (Yang, 2016; Anokhin et al,. 2009), and weak property rights (Baldwin and Gellatly, 2004). Additionally, Demirbas et al. (2011) concludes that the tendency to innovate in Turkey is hampered by the informal economy because it has a negative impact on investments and on channeling innovation. Moreover, a report conducted by the Inter-American Development Bank (2002) states that paperwork and regulatory impediments are frequently encountered as obstacles by firms for entrepreneurships. To this end, this paper will investigate answers related with labor regulations and business licensing permits that will provide us an insight as to whether they restrain the act of innovation. Furthermore, Anokhin et al., (2009) argue that corruption harms trust and this raises transaction costs that can obstruct innovation and entrepreneurship. Additionally, from the supplementary view, Yang (2016) asserts that a better court system is strongly associated with innovative activities due to the fact that it is such potent institutions and courts that ensure a stable patent system and protection of ideas. Lastly, Waguespack et al., (2005) conclude that political stability matters for innovation and national political conditions especially shape the patenting behavior. In this paper, apart from other factors that are explained below, we attempt to investigate how a governance environment that is measured by several variables affects the innovation activities of SMEs in Turkey.

2.2. Firm Characteristics

In addition to the external environment, firm characteristics might also play a role in being a potential innovator. The positive impact of firm size on R&D has already been captured in early studies (see Fisher et al., 1973; Dosi, 1998). Also, Cirera et al. (2016) empirically analyzing the innovation enterprise survey data in Sub-Saharan Africa and South Asia states that firm size is negatively correlated with innovation activity due to the accumulated knowledge in larger firms.

Furthermore, Schreyögg et al. (2007) argue that reforming the organizational setting in long-standing SMEs might be time-consuming and more costly compared to the newly established ones which do not have strict and entrenched operations. On the other hand, Lumpkin et al. (1996) asserts that younger firms are flexibile to generate new operations and techniques that are hard to replicate or switch, which therefore, results in having a competitive advantage. Also, a meta-analysis conducted by Rosenbusch et al. (2011) demonstrates that innovation activity is more found in new ventures than in mature firms. With the firm level-analysis in Malaysia, Cassey (2004) concludes that firms which have legal status as limited liability company are more likely to innovate compared to sole proprietorship firms and he argues that this could be the case as limited liability companies have greater access to the financial resources (e.g. equity market.) Thus, in this paper we also attempt to investigate if firms' characteristics (including size, maturity and the ownership structure) matter for innovativeness or not.

2.3. Other Factors Behind Innovation

Radas et al. (2009) mention that those establishments who are involved in international trade would be more motivated to innovate because of the strong competition they face. That is to say, Sorescu et al. (2013) claims that there is a greater motivation if there is competition.

Furthermore, employees' intellectual capital is closely linked to a firm's products and services; thus, the ability of a firm to introduce new products or services is dependent on its human capital. There are a few studies that indicated experienced entrepreneurs are more inclined to innovate than those who are less experienced (Romijn et al., 2002) although Avermaete et al. (2004) do not find a significant relationship between experience and innovativeness.

In terms of the role of financial grants, there is no consensus in the literature.[1] Lastly, we seek an answer as to whether female ownership is an important indicator for innovation or not in the Turkish context. Palalic et al. (2016) demonstrated that females perform considerably better than their male counterparts in terms of innovativeness in a study made within Bosnian SMEs.

Following these, in this paper, we attempt to make a valuable contribution to the knowledge of SMEs in Turkey, in terms of understanding the factors behind their innovativeness using firm-level data. As mentioned above, SMEs contribute more than two thirds of employment in Turkey. But on the other hand, the total value added (57%) is much less than its employment contribution and this difference is considerably high when compared to other countries (OECD, 2010). According to Inel et al. (2013) the difference illustrates evidence of a low level of labor productivity and they suggest product innovation can help narrow the gap. Ayyagari et al. (2014) also asserted that possible policy suggestions for entrepreneurship and innovation will be significant especially for developing countries.

3. Data and Methodology

This section reviews the data and key variables which will be used in the empirical analysis of this paper. The firm-level data which is used in this study was all collected from cities in Turkey and compiled in the World Bank's Regional Enterprise Survey (R-ES) in 2015 and 2016. In total, 6,006 establishments took part in the interview and the target number of sampling was achieved. The aim of the R-ES was to have comprehensive information about Turkish firms' experience and their opinions related with the business environment in Turkey. Information about variable definitions and the sample can be found in Figure 1 and Figure 2, and Table 1A, Table 2A and Table 3A in the Appendix. Figure 1 shows the number of firms according to their scale which is measured by employee number and Figure 2 indicates how many firms are considered to be innovators.

1 Birchall et al. (1996), Le Blanc et al. (1997) and Hoffman et al. (1998), for example, conclude differently about the role of grants on innovativeness.

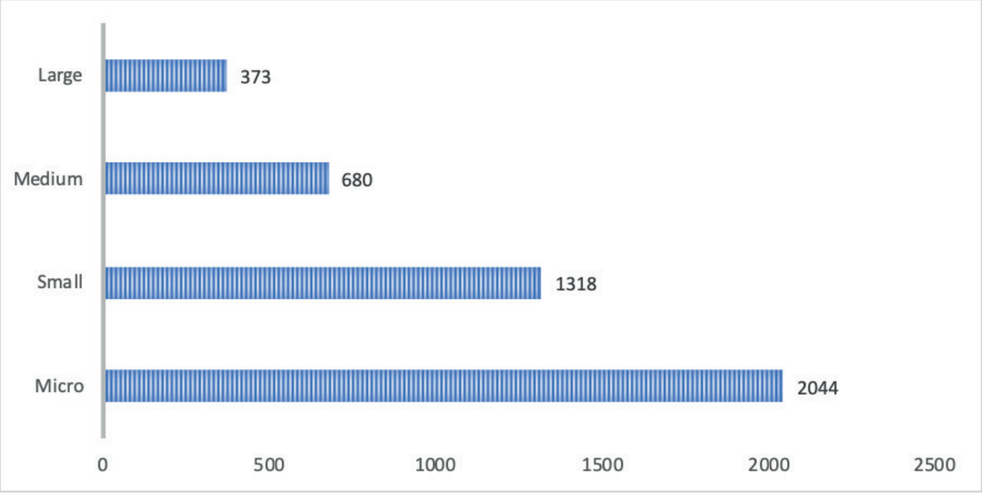

Figure 1. Distribution of Firms by their size.
(Total: 4,412 Firms. Source: World Bank Turkey R-ES Data, 2015)

Sample selection was designed as stratified random sampling due to the fact that it has lots of advantages such as having lower standard errors in population estimates compared to simple random sampling, achieving unbiased estimates for each subdivision of population with a considerable level of precision and lowering costs per observation in survey via grouping the population.

The sample is segmented by establishment size, industry and region. Size is stratified into micro, small, medium and large according to the establishment's employee numbers. Industry stratification was carried out for manufacturing industries and service industries in the context of their various activities such as textiles and construction etc. Although agriculture has some level of importance in Turkey's economy by representing 7% of Turkey's GDP, the survey data does not cover this sector. Therefore, our representative sample will contain only non-agricultural sectors (World Bank, 2016). Lastly, region is stratified into 26 'NUTS 2' regions[2] and the data covers the whole private sector geographically between 2015 and 2016.

The dependent variable 'innovator' is created by the survey question which seeks to answer whether or not the establishment introduced new or significantly improved products or services in the last three years. Moreover, this question is aligned with the definition of innovation in the literature review. Thus, it is a binary variable, which takes the value 1, if the

2 NUTS: Nomenclature of Territorial Units for Statistics. Turkey, as being candidate country to European Union, it also adopted NUTS classifications and it has 12 Regions in NUTS-1, 26 subregions in NUTS-2 and 81 provinces in NUTS-3. (Eurostat, 2016)

firm innovates; or takes the value of 0 zero if the firm does not innovate. As Figure 2 shows, the majority of firms in the sample are not marked as having innovative activity in their production, which is in line with the lower value-added contribution of SMEs in Turkey relative to their employment capacity. Logit regression is employed in the empirical analysis due to the structure of the dependent variable. Table 3A provides the definitions of other control variables which are also used in the literature as mentioned above.

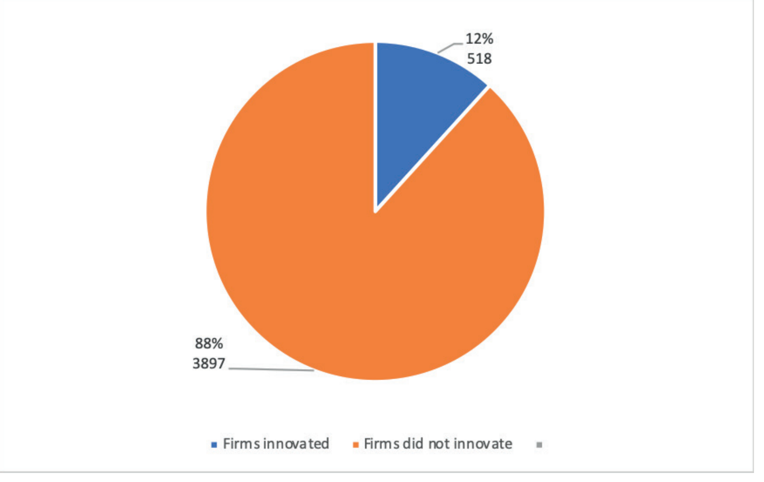

Figure 2. Distribution of Firms by innovativeness.
(Total: 4,412 Firms. Source: World Bank Turkey R-ES Data, 2015)

The tendency to innovate is modelled as:

$$y_i^* = X_i^{'}\beta + \mu_i \tag{1}$$

where;

$$Y_i = \begin{cases} 1, & innovate \\ 0, & does\ not\ innovate \end{cases} \tag{2}$$

μ_i corresponds to the error term and $X_i^{'}$ refers to the group of explanatory variables. The bundle of explanatory variables are selected in reference to the previous studies and the availability of data.

The logit model is applied to the likeliness of innovation as:

$$prob\ (y_i = 1) = \frac{e^{Xi\beta}}{1 + e^{Xi\beta}} \tag{3}$$

where; $Xi\beta = a + b_2X_{2i} + b_3X_{3i} + \cdots + b_kX_{ki}$

The following equation is a demonstration of a final model:

$$\Pr(innovator = 1) = F(\beta_0 + \beta_1 \log(\text{firm age}) + \beta_2 \text{large firm} + \beta_3 \text{soleproprietorship} +$$

$$\beta_4 \text{experience of top manager} + \beta_5 \text{internet connection} + \beta_6 \text{exporter} +$$

$$\beta_7 \text{government grant} + \beta_8 \text{female ownership} + \beta_9 \text{corruption} + \beta_{10} \text{courts} +$$

$$\beta_{11} \text{business licensing and permits} + \beta_{12} \text{labor regulation})$$

where; $(X_i^{'}\beta)$ cumulative logistic distribution. Table 3 presents the descriptive statistics of the variables in the empirical model.

Table 3. Descriptive Statistics.

Variables	N	Mean	Std. Dev.	Min	Max
Innovator	4,412	.117	.322	0	1
Firm Characteristics					
Firm Age (log)	4,412	2.400	.808	0	5.075
Firm Size					
Micro Firm	4,412	.463	.498	0	1
Small Firm	4,412	.298	.457	0	1
Medium Firm	4,412	.153	.360	0	1
Large Firm	4,412	.084	.278	0	1
Legal Status of Firm					
Limited Liability Company	4,412	.253	.435	0	1
Sole Proprietorship	4,412	.662	.472	0	1
Other type of firm	4,412	.083	.277	0	1
Experience of Top Manager	4,412	20.15	10.69	1	68
Internet Connection	4,412	.657	.475	0	1
Exporter	4,412	.0639	.245	0	1
Government Grant	4,412	.0401	.196	0	1
Female Ownership	4,412	.129	.335	0	1
Governance Environment					
Access to finance	4,412	.146	.353	0	1
Access to land	4,412	.011	.104	0	1
Business licensing and permits	4,412	.029	.167	0	1
Corruption	4,412	.021	.145	0	1
Courts	4,412	.003	.061	0	1
Crime theft	4,412	.009	.099	0	1
Customs and trade	4,412	.017	.131	0	1
Electricity	4,412	.020	.141	0	1
Inadequately educated workforce	4,412	.112	.316	0	1
Labor regulations	4,412	.041	.198	0	1
Political instability	4,412	.107	.310	0	1
Practices of competitors in the informal sector	4,412	.109	.312	0	1
Tax administration	4,412	.041	.199	0	1
Tax rates	4,412	.029	.453	0	1
Transport	4,412	.036	.186	0	1

4. Empirical Findings

This section tests the hypotheses mentioned in Section 2. Table 4 provides the marginal effects of the logit regression, from the nested models to the full model above.

Table 4. Marginal effects after logit model (dependent variable: dummy variable for innovation).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Firm Characteristics							
log(firm_age)	.009 (.015)	.003 (0.01)	.003 (.010)	.001 (.008)	.000 (.008)	.000 (.008)	000 (.008)
Firm Size (Reference Category: Micro Firm)							
Small Firm	.051*** (.010)	.050** (.009)	.024** (.011)	.023* (.012)	.023* (.012)	.024** (.011)	.019 (.013)
Medium Firm	.069*** (.007)	.068** (.007)	.031*** (.002)	.021** (.009)	.014 (.012)	.013 (.012)	.006 (.012)
Large Firm	.163*** (.012)	.165** (.014)	.101*** (.005)	.067*** (.012)	.055*** (.009)	.054*** (.011)	.004*** (.013)
Legal Status of Firm (Reference Category: Limited Liability Company)							
Sole Proprietorship	-.046*** (.021)	-.045*** (.019)	-.027** (.013)	-.022** (.008)	-.018** (.005)	-.016*** (.004)	-.019*** (.004)
Other type of firm	.034 (.010)	.033*** (.010)	.032*** (.008)	.022 (.015)	.022* (.013)	.021 (.013)	.020 (.012)
Experience of Top Manager		.001* (.000)	.001* (.000)	.000* (.000)	.000 (.000)	.000 (.000)	.000 (.000)
Internet Connection			.077** (.025)	.075** (.022)	.074** (.022)	.074*** (.021)	.070*** (.019)
Exporter				.116** (.033)	.097*** (.035)	.097*** (.037)	.100*** (.033)
Government Grant					.105*** (.028)	.100*** (.031)	.094*** (.299)
Female Ownership						.025 (.018)	.026 (.020)
Governance Environment (Reference Category: Practices of competitors in the informal sector)							
Access to finance							-.040* (.023)
Access to land							-.035 (.044)
Business licensing and permits							.000 (.009)
Corruption							-.042*** (.008)
Courts							.039 (.031)
Crime theft							-.049 (.042)

Customs and trade							-.028* (.015)
Electricity							-.051*** (.013)
Inadequately educated workforce							-.016 (.021)
Labor regulations							-.026*** (.004)
Political instability							-.032 (.022)
Tax administration							-.020 (.013)
Tax rates							-.044** (.020)
Transport							-.051*** (.017)
Regional Effect	X	X	X	X	X	X	X
# of obs	4412	4412	4412	4412	4412	4412	4412
N-Clusters	2	2	2	2	2	2	2
Notes: Standard errors in parantheses, ***p<0.01, **p<0.05, *p<0,1.							

The marginal effects demonstrate that firm age is not found as statistically significant for determining innovation activities in Turkish SMEs. In addition to that, large firms (those employing more than 100 employees), are 0.4 percent more inclined to be involved in innovation activities, when compared to micro firms which employ less than 5 employees. However, small and medium firms, compared to micro firms, do not establish a statistically important result in terms of innovativeness.

Furthermore, the regression results attest to the idea that the type of ownership matters for innovation involvement for Turkish SMEs. Having a legal status as sole proprietor results in a 1.9 percent lower probability of innovation activity for an establishment when it is compared to firms that have an ownership type as limited liability; which is consistent with the literature review.

The marginal effects also assert that introducing the main products or services to the international market, i.e. being an exporter, is found to be statistically significant and increases the odds of being involved in innovation by 10 percent when keeping all other control variables constant. In addition, obtaining a grant from the government increases the probability of engagement with innovation by 9.4 percent for Turkish SMEs, in ceteris paribus. As can be seen in Table 4, having an internet connection increases the likelihood of introducing new or significantly advanced products or processes to the market by 7 percent which is also in line with previous studies. Moving on to gender, in the data those firms that had at least one female in their ownership structure was only 12.8% which is very low. Nevertheless, the establishments that are in this small proportion are 2.6 percent more inclined to exercise tasks related to innovation.

In the empirical analysis, some of the negative perceptions about governance environment are found to be very important and powerful in explaining the innovativeness of Turkish SMEs. Firstly, being interesting for the research, those firms which perceive corruption and which identify labor regulations as the biggest obstacle are found less likely to be innovators than the firms which perceive practices of competitors in the informal sector as a key hindrance by 4.2 percent and 2.6 percent, respectively. Moreover, establishments that identify access to finance as the biggest impediment are 4 percent less inclined to engage in innovation than establishments that find the practices of competitors in the informal sector as the biggest obstacle. Also, the firms that recognize tax rates and transport as a key impediment are less motivated to innovate by 4.4 percent and 5.1 percent, respectively, relative to firms that find exercises of rivals in the informal sector as the biggest obstacle. On the other hand, interestingly, political instability and business licensing processes do not significantly affect innovation activity.

Lastly, the experience level of top tier management does not significantly affect innovativeness, either. Regional variables are salient controls yet they have little influence in our final model. The variations of governance climate at a regional level is provided by Enterprise Surveys firm-level data which is beneficial for the research.

The goodness of fit which is measured by Pseudo R2, increases when it approaches the final model, indicating that the full model is more explanatory than the nested models. Nevertheless, predicting the probability of being an innovator seems to be weak for the model which indicates there are other crucial factors that impact the dependent variable which do not exist, unfortunately, in our data set.

Moreover, the VIF scores of all variables are found at acceptable levels and no VIF score exceeds 2.0. As these findings fit within the boundary of currently confirmed standards (VIF\10.00), they support that variables in the models are free from multicollinearity (Hair et al. 2006).

Also, the data sampled from manufacturing and service sectors engender clusters within sectors. So, because of the fact that outcomes within a cluster have a high probability to be correlated (Wooldridge, 2009), the analysis has been made with clustering. As a result, standard errors, usual test statistics and heteroscedasticity are corrected overall within cluster correlation.

Results with and without clustering are shown in Table 4A and Table 5A, and overall the standard errors are found less when the clustering is employed. Results are similar to Table 2.

5. Conclusion

Vital contributions are made by SMEs in terms of economic dynamism in Turkey. So much so, SMEs which are involved in innovation are often thought to be leading factors for economic growth. Economists and policymakers alike are driven by this concept and try to motivate businesses to innovate. In this context, this study analyzes the underlying factors of innovation for Turkish SMEs, using firm-level data.

Our analysis finds that being a larger-scale firm increases the likelihood of being an innovator. Therefore, transfer of knowledge to smaller-size businesses through an organized exchange of information could improve the entrepreneurship environment and help the overall economy. Also, having sole proprietorship in Turkish SMEs reduces the probability of being an innovator compared to limited liability firms. Although it is more common to have sole proprietorship in the first phases of the establishment, it would be, thus, better if the firms were encouraged to alter their ownership structure to limited liability. In addition, foreign experience allows Turkish SMEs be more competitive, helping them create newer products or processes. Hence, potential tax exemptions and easing of customs and trade regulations could help them make new inroads to overseas markets, eventually enabling them to become more innovative. Moreover, adoption of the Internet and similar communication technologies may help Turkish SMEs to innovate more, and even it leads to a multiplier effect by increasing their presence in the international markets. Likewise, government grants appear to encourage innovation; therefore, there needs to be further policy improvement for dedicating funds to SMEs in Turkey. Interestingly, gender in ownership does matter for innovation according to our regression results which indicates that further encouragement for women entrepreneurs may also play a positive role in overall innovation capacity.

Furthermore, it was found that Turkish SMEs' innovativeness is hindered by some governance climate characteristics. As a policy suggestion, ameliorating the contractual environment and enhancing the ease of doing business would promote an environment for entrepreneurs in Turkish SMEs. Regulatory obstacles, specifically labor regulations, are found to be impairing the firms' involvement in innovation. Also, corruption appears to decrease the innovativeness of Turkish SMEs; thus, a reduction of frequency and the size of "additional payments to get things done" might encourage businesses to introduce new or significantly improved products/services.

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Appendix

Table 1A. Regions that are defined in the data and the number of firms which are surveyed in those regions.

NUTS 2 REGION	Province(s)	Number of firms
TR10	(İstanbul)	862
TR31	(İzmir)	72
TR41	(Bursa, Eskişehir, Bilecik)	182
TR42	(Kocaeli, Sakarya, Düzce, Bolu, Yalova)	186
TR51	(Ankara)	144
TR61	(Antalya, Isparta, Burdur)	94
TR21	(Tekirdağ, Edirne, Kırklareli)	98
TR22	(Balıkesir, Çanakkale)	52
TR32	(Aydın, Denizli, Muğla)	206
TR33	(Manisa, Afyon, Kütahya, Uşak)	202
TR52	(Konya, Karaman)	119
TR62	(Adana, Mersin)	118
TR72	(Kayseri, Sivas, Yozgat)	83
TR81	(Zonguldak, Karabük, Bartın)	74
TR83	(Samsun, Tokat, Çorum, Amasya)	206
TR63	(Hatay, Kahramanmaraş, Osmaniye)	184
TR71	(Kırıkkale, Aksaray, Niğde, Nevşehir, Kırşehir)	137
TR82	(Kastamonu, Çankırı,Sinop)	92
TR90	(Trabzon, Ordu, Giresun, Rize, Artvin, Gümüşhane)	298
TRA1	(Erzurum, Erzincan, Bayburt)	104
TRB1	(Malatya, Elazığ, Bingöl, Tunceli)	106
TRC1	(Gaziantep, Adıyaman, Kilis)	145
TRA2	(Ağrı, Kars, Iğdır, Ardahan)	127
TRB2	(Van, Muş, Bitlis, Hakkari)	167
TRC2	(Şanlıurfa, Diyarbakır)	191
TRC3	(Mardin, Batman, Şırnak, Siirt)	163
Total		4412

Table 2A. Industry of firms in the survey data	
Industry	**Number of firms**
Food	564
Textiles and Germents	542
Fab metal, machinery, motor vehicles	461
Other manufacturing	577
Construction	470
Wholesale and Retail	862
Transport	476
Other Services	460
Total	4412

Table 3A. Variable Definitions. (The data collected between August 2015 and June 2016)	
Variables	Definition
Innovator	Dummy variable which takes the value 1 if the establishment reported new or significantly improved products or services during the last three years.
Firm Characteristics	
log(firm_age)	The logarithm of firm's age (in years).
Firm Size	
Micro Firm	Dummy variable which takes the value 1 if the establishment have less than 5 employees.
Small Firm	Dummy variable which takes the value 1 if the establishment have more than 5 employees and less than 19 employees
Medium Firm	Dummy variable which takes the value 1 if the establishment have more than 20 employees and less than 99 employees
Large Firm	Dummy variable which takes the value 1 if the establishment have more than 100 employees.
Legal Status of Firm	
Limited Liability Company	Dummy variable which takes the value 1 if the legal form of the establishment is limited liability company
Sole Proprietorship	Dummy variable which takes the value 1 if the legal form of the establishment is sole proprietorship.
Other type of firm	Dummy variable which takes the value 1 if the legal form of the establishment is not sole proprietorship or limited liability company.
Managerial Characteristics	
Experience	Years of experience of top manager in the given sector.
Internet Connection	Dummy variable which takes the value 1 if the establishment has an internet connection.
Exporter	A dummy variable which takes the value 1 if the establishment directly exported its products in 2004.

Government Grant	A dummy variable which takes the value 1 if the establishment received any direct or indirect government grant in last two years.
Female ownership	Dummy variable which takes the value 1 if the establishment has at least one female owner.
Governance Environment	
Access to finance	Dummy variable which takes the value 1 if establishment reports “access to finance” as the biggest obstacles it faces.
Access to land	Dummy variable which takes the value 1 if establishment reports “access to land” as the biggest obstacles it faces.
Business licensing and permits	Dummy variable which takes the value 1 if establishment reports “business licensing and permits” as the biggest obstacles it faces.
Corruption	Dummy variable which takes the value 1 if establishment reports “corruption” as the biggest obstacles it faces.
Courts	Dummy variable which takes the value 1 if establishment reports “courts” as the biggest obstacles it faces.
Crime theft	Dummy variable which takes the value 1 if establishment reports “crime theft” as the biggest obstacles it faces.
Customs and trade	Dummy variable which takes the value 1 if establishment reports “customs and trade” as the biggest obstacles it faces.
Electricity	Dummy variable which takes the value 1 if establishment reports “electricity” as the biggest obstacles it faces.
Inadequately educated workforce	Dummy variable which takes the value 1 if establishment reports “inadequately educated workforce” as the biggest obstacles it faces.
Labor regulations	Dummy variable which takes the value 1 if establishment reports “labor regulations” as the biggest obstacles it faces.
Political instability	Dummy variable which takes the value 1 if establishment reports “political instability” as the biggest obstacles it faces.
Practices of competitors in the informal sector	Dummy variable which takes the value 1 if establishment reports “practices of competitors in the informal sector” as the biggest obstacles it faces.
Tax administration	Dummy variable which takes the value 1 if establishment reports “tax administration” as the biggest obstacles it faces.
Tax rates	Dummy variable which takes the value 1 if establishment reports “tax rates” as the biggest obstacles it faces.
Transport	Dummy variable which takes the value 1 if establishment reports “transport” as the biggest obstacles it faces.

Table 4A. Clustered Full Model

Clustered Full Model	**Odds Ratio**	**Standard Error**
Firm Characteristics		
log(firm_age)	1.008	.126
Firm Size (Reference Category: Micro Firm)		
Small Firm	1.311	.322
Medium Firm	1.102	.214
Large Firm	1.668***	.418
Legal Status of Firm (Reference Category: Limited Liability Company)		
Sole Proprietorship	.763***	.001
Other type of firm	1.31	.285
Experience of Top Manager	1.01	.004
Internet Connection	3.235***	.026
Exporter	2.743**	.199
Government Grant	.386***	.149
Female Ownership	.710**	.111
Governance Environment (Reference Category: Practices of competitors in the informal sector)		
Access to finance	.484***	.132
Access to land	.504	.469
Business licensing and permits	1.001	.145
Corruption	.408***	.039
Courts	1.604**	.346
Crime theft	.317	.362
Customs and trade	.598***	.104
Electricity	.295***	.014
Inadequately educated workforce	.769	.227
Labor regulations	.628***	.038
Political instability	.566**	.160
Tax administration	.709**	.102
Tax rates	.477***	.076
Transport	.314***	.036
Regional Effect	X	
Pseudo R2	0.181	
# of obs	4412	
N-Clusters	2	
Notes: Standard errors are in parenthesis, ***p<0.01, **p<0.05, *p<0.1		

Table 5A. Unclustered Full Model

Unclustered Full Model	**Odds Ratio**	**Standard Error**
Firm Characteristics		
log(firm_age)	1.005	.073
Firm Industry (Reference Category: Manufacturing)		
Service	.590***	.066
Firm Size (Reference Category: Micro Firm)		
Small Firm	1.197	.175
Medium Firm	1.012	.189
Large Firm	1.585**	.332
Legal Status of Firm (Reference Category: Limited Liability Company)		
Sole Proprietorship	.742**	.106
Other type of firm	1.257	.212
Experience of Top Manager	1.010**	.005
Internet Connection	3.397***	.547
Exporter	2.460**	.433
Government Grant	.413***	.085
Female Ownership	.735**	.107
Governance Environment (Reference Category: Practices of competitors in the informal sector)		
Access to finance	.500***	.107
Access to land	.534	.333
Business licensing and permits	1.151	.346
Corruption	.390**	.182
Courts	1.499	.905
Crime theft	.347	.281
Customs and trade	.583*	.180
Electricity	.297**	.158
Inadequately educated workforce	.745	.141
Labor regulations	.632	.182
Political instability	.590**	.128
Tax administration	.727	.214
Tax rates	.487***	.087
Transport	.317***	.130
Regional Effect	X	
Pseudo R2	0.188	
# of obs	4412	
N-Clusters	0	
Notes: Standard errors are in parenthesis, ***p<0.01, **p<0.05, *p<0.1		

CHAPTER 2

TECHNOLOGICAL INNOVATION CAPACITY AND ECONOMIC GROWTH NEXUS

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Abstract

As suggested by the literature on endogenous growth, technological innovation plays a significant role in economic growth. The goal of this study is to explore the empirical link between technological innovation capacity and economic growth over the period between 2000 and 2016. By utilizing panel-type econometric models, we specifically ask whether a number of indicators such as research and development expenditures, patent applications and high-technology exports as the proxy of innovation play a role in the GDP formation of 20 developed and developing countries. The evidence suggests that total patent applications growth, total labor force growth and gross capital formation growth are statistically significant and positively correlated with economic growth. Our results suggest interesting policy implications for the long-term growth and competitiveness benefits of investing in technological innovation capacities and also some important insights into how investment in human capital may contribute to an increase in economic growth.

Keywords: Innovation, competitiveness, economic growth, endogenous growth theory.

JEL Classifications: G32, L10, O31, P20.

1. Introduction

Human history teaches us, however, that economic growth springs from better recipes, not just from more cooking. New recipes produce fewer unpleasant side effects and generate more economic value per unit of raw material.[1]

Paul Romer (2018 Nobel Prize Winner)

Economic growth is defined as an increase in the total output produced in a country, including both goods and services in a period of time. The higher the produced output is, the wealthier the country is. It means more consumption, export, wealth and prosperity. Therefore, determinants of economic growth are important for the maintenance of economic prosperity. Many classical economists have argued that economic growth was determined by a few factors such as labor, agricultural production and exports and generating surplus and its reinvestments are the essential part of classical economic growth theory. Therefore, the success of the economic growth process depends on the reinvestment of this surplus.

Quesnay (1758, 1972) was the first who suggested that agriculture was the only sector capable of generating a surplus. According to Adam Smith, the manufacturing sector and commerce were also capable of producing profits and the returns in agriculture were diminishing. The diminishing returns in agriculture was a key aspect of Malthus' theory (1798) of population. Thus, agriculture was classically accepted as the fundamental sector for growth process. Eltis (2000) stated that according to Quesnay, surplus was the excess of agricultural output over wages and farmers' necessary costs. For Smith (1776, 2010) and Ricardo (1891) it was the excess of output over wages in industry, agriculture and commerce while it was the excess of output over wages in industry and agriculture alone for Marx (1849). Most studies in the field of classical theory of economic growth have focused only on the question of where surplus springs from. The study of the determinants of economic growth was first carried out by Solow (1956) from a different point of view to that of neoclassical growth theory. In Solow's model, output per labor was explained by the number of qualified labor instead of population and capital formation per labor. Moreover, Solow suggested that an unexplained variation in economic growth was dependant on technological innovations. In other words, technological innovation was an exogenous variable in Solow's model.

1 See, https://paulromer.net/economic-growth/ (Romer, (undated). accessed on 08/26/2019).

In the literature on endogenous economic growth theory, the relative importance of technological innovations has been subject to considerable debate. As Romer (undated) states, new technologies generate more economic value per unit of raw material and leads to an increase in economic growth. Knowledge, knowledge spillovers, increase in human capital, increase in research and development expenditures, and patent laws may contribute to development and sustainable economic growth. As mentioned in Pack (1994), endogenous growth theory has the advantage of attempting to explain the forces that give rise to technological change, rather than following the assumption of neoclassical growth theory that says such change is exogenous.

This study focuses on the effects of an increase in technological capacity of a country on its economic growth. In particular, we examine whether a number of indicators such as research and development expenditures, patent applications and high-technology exports as the proxy for innovation play a central role in the GDP formation. We also use renewable energy consumption as an explanatory variable where energy is an essential factor in a typical production process and any improvement in the usage of energy may provide a reduction in production costs. Moreover, increasing demand for energy has severe environmental implications such as climate change. As it is stated by Irandoust (2016), it is widely believed that renewable energy as an almost carbon free energy source can serve as a potential solution to both energy safety and climate change problems. However, from another point of view, an improvement in the efficiency of energy consumption may lead to a kind of paradoxical outcome. As it is emphasized in Clark and Foster (2001), Jevons (1865) claimed that an increase in efficiency in the usage of a natural resource, such as coal, only generates an increased demand for that resource, not a decreased demand as one might expect. This was because improvement in the efficiency of that resource led to further economic expansion. Therefore, we included both renewable energy consumption and CO2 emissions in our model to investigate whether or not the improvements in the efficiency of energy resources as an innovation in energy consumption influence GDP growth in a paradoxical way as Jevons (1865) suggested. Moreover, Jevons' paradox also implies that increased efficiency of a resource leads to an increased demand for that resource and further economic expansion. As a result it also gives rise to an increase in environmental issues in particular climate change depending on the increased demand of energy.

Our analysis contributes to the existing literature by including several variables in the same regression model for both developed and developing countries. The study is organized as follows. We first provide a brief overview of the theoretical background of economic growth and a literature review in Section 2. Section 3 is concerned with the data and methodology used for this study. Section 4 presents the findings of the research. Finally, the conclusion section gives a brief summary and critique of the findings.

2. Theoretical Background and Literature Review

The first serious discussions and analyses of economic growth emerged during the 1950s with Solow (1956). Neoclassical growth theory, as developed by Solow (1956) suggests that net output is produced with the help of two factors of production: capital and labor. Represented by a production function, technological possibilities show constant returns to scale as seen below:

$$Y = F(K,L) \tag{1}$$

According to Solow, an economy with an initially low capital-labor ratio will have a high marginal product of capital (Grossman and Helpman, 1994). As stated in Romer (1994), a simple version of the neoclassical model can be expressed in the Cobb-Douglas production function below:

$$Y = A(t)K^{1-\beta} L^{\beta} \tag{2}$$

where Y denotes net national product, K denotes the stock of capital, L denotes the stock of labor and A denotes the technological capacity in equation (1) and equation (2). In equation (2), β and 1- β denote the elasticities of labor and capital, respectively. In the neoclassical growth model, technological changes are exogenous and cannot be explained by the model.

Under perfect competition in the final goods market and under the assumption of constant returns to scale, β and 1- β should be equal to the shares of capital and labor in national income, respectively, that is 1/3 and 2/3 approximately in the U.S. case. However, Romer (1987) estimated the elasticities to be higher than the value predicted by Solow model (Aghion and Howitt, 1998). After the 1960s, more attention was focused on the effects of technological progress and innovations on economic growth. Several attempts have been made to explain the role of technological development as an endogenous factor on economic growth. “Endogenous growth theory” emerged in the 1980s with a growing body of theoretical and empirical literature (i.e., Arrow, 1962; Romer, 1986, 1987, 1990; Lucas, 1990, 1993). Endogenous growth theory suggested that not only the accumulation of capital, but mainly the development and accumulation of knowledge and technological change leads to increased and sustainable growth (Kokkinou, 2011). Romer (1987, 1990) investigated the role of knowledge and knowledge spillovers on sustainable growth. Based on Romer’s model

(1990), an economy with a larger total stock of human capital will experience faster growth. The results also suggest that free international trade can act to speed up growth. Krugman (1991) also found evidence for the impact of knowledge spillovers on the increasing returns and growth rate. Mankiw et al. (1992) found that the rate at which countries converge to their steady states is slower than that predicted by a Solow model with a capital share of 1/3. The empirical results suggest a share of broad capital in output of around 0.7-0.8. The Solow model was augmented to include a role for human capital (H) specified in the following production function (Aghion and Howitt, 1998):

$$Y = K^{\alpha}H^{\beta}(AL)^{1-\alpha-\beta} \quad (3)$$

Where Y is output, K is the stock of capital, H is human capital, A is technological capacity and L is labor. As it can be seen from equation (3), it is assumed that returns to scale is constant.

Barro (1991) states that human capital plays a special role in a number of models of endogenous economic growth. As Nelson and Phelps (1966) and Romer (1990) suggested, human capital generates new products and new ideas which underlie technological progress. Long-run growth was explained by focusing on technological progress and R&D in several studies such as Romer (1990), Grossman and Helpman (1991a, 1991b) and Aghion and Howitt (1992) in the endogenous growth literature. In these models, technological progress results from the search for innovation and the discovery of an innovation raises productivity, and such discoveries are ultimately the source of long-term growth (Jones, 1995).

To examine technological change in Britain since 1870, Nicholas (2012) analyzed the effects of patent laws and innovation prizes that were designed to promote technical progress. Although Britain improved productivity growth from the early 1970s, the evidence supports the traditional story of British failure in generating large payoffs from technological development. Petrariu et al. (2013) examined the empirical evidence on the link between innovation and economic growth in Central and Eastern European countries (CEE). The results of their study indicate that innovation makes a significant contribution to national competitiveness and economic growth and the gap between the Western and Eastern economies can be reduced by investing in innovation. Inekwe (2015) examined the role of R&D spending on the economic growth of developing economies. The results reveal that the effect of R&D spending on growth is positive for upper middle-income economies while insignificant in lower income economies. Ciocanel and Pavelescu (2015) tested the links between innovation and competitiveness. The results of the study indicate that improving innovation performance leads to an increase in national competitiveness and economic growth. Pece et al. (2015) analyzed whether the long-term economic growth is influenced by the innovation potential of an economy for CEE countries (Poland, Hungary and Czech Republic). In order to quantify the innovation, they selected various variables such as number of patents, number of trademarks, and R&D expenditure. Their results suggest that there is a positive relationship between economic growth and innovation.

Gumus and Celikay's dynamic panel data model (2015) for 52 countries showed that R&D expenditure has a positive and significant effect on economic growth in the long run, which is consistent with the relevant literature. However, for developing countries, the effect is weak in the short run but strong in the long-run, as expected. A study by Irandoust (2016) examined the relationship between renewable energy consumption, technological innovation, economic growth, and CO2 emissions in the four Nordic countries (Denmark, Finland, Norway and Sweden). A modified version of the Granger non-causality test was employed in the study in order to analyze the causality among the selected variables. The results show a unidirectional causality running from renewable energy to CO2 emissions for Denmark and Finland and a bidirectional causality between these variables for Sweden and Norway. The findings also indicate a unidirectional causality running from technological innovation to renewable energy and from growth to renewable energy for the four Nordic countries. Interestingly, the results could not confirm any causality from renewable energy to economic growth.

Another work on energy consumption and growth nexus was undertaken by Antonakakis et al. (2017). They used the data on energy consumption (and its subcomponents), carbon dioxide emissions and real GDP in 106 countries classified by different income groups over the period from 1971 to 2011. The results of the study reveal that the effects of the various types of energy consumption on economic growth and emissions are heterogeneous on the various groups of countries. They could not report any statistically significant evidence that renewable energy consumption leads to economic growth. This finding implies the fact that renewable energy consumption is not able to promote growth in a more efficient and environmentally sustainable way. Terzic (2017) investigated the role of innovation in developing economies. Findings reveal that the economic growth and competitiveness of developing economies are powerfully connected to their innovation status. Akinwale (2018) analyzed the short- and long-run relationships between energy consumption, technology innovation and economic growth in Saudi Arabia. The study reveals that policy makers are required to form policies that will continue to encourage government investment in R&D that would generate technology innovation so as to reduce the extent of energy consumption.

3. Data and Modelling Strategy

3.1. Data

For the empirical analysis, we used real per capita GDP growth as the dependent variable. Our main independent variables are R&D expenditure as a percentage of the GDP and total patent applications (residents and nonresidents). We also used several control variables which are widely used in the empirical literature such as high-technology exports as a percentage of manufactured exports, labor force, gross capital formation per labor, CO2 emissions (kg per GDP 2010 US$ of GDP), and renewable energy consumption as a percentage of total final energy consumption. We use a panel dataset involving 20 developed and developing countries[2] during the period of 2000-2016. Data for all variables was compiled from the World Development Indicators database[3]. GDP per capita and gross capital formation per labor are expressed in constant 2010 US$ prices. The model was estimated using all variables in their first differences. Table 1 describes the variables.

Table 1: The Variables Used in the Models

Variables	Definition
GDP per capita (constant 2010 US$) (GDP)	GDP per capita is gross domestic product divided by mid-year population. GDP is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products.
Research and development expenditure (% of GDP) (RDE)	Gross domestic expenditures on research and development (R&D), expressed as a percent of GDP. They include both capital and current expenditures in the four main sectors: business enterprise, government, higher education and private non-profit. R&D covers basic research, applied research, and experimental development.
Total Patent Applications (TPA)	Patent applications are worldwide patent applications filed through the Patent Cooperation Treaty procedure or with a national patent office.
High-technology exports (% of manufactured exports) (HTE)	High-technology exports are products with high R&D intensity, such as in aerospace, computers, pharmaceuticals, scientific instruments, and electrical machinery.
Labor force, total (TLF)	Labor force comprises people aged 15 and older who supply labor for the production of goods and services during a specified period. It includes people who are currently employed and people who are unemployed but seeking work as well as first-time job-seekers. Not everyone who works is included, however. Unpaid workers, family workers, and students are often omitted, and some countries do not count members of the armed forces. Labor force size tends to vary during the year as seasonal workers enter and leave.

2 Selected countries are Austria, Belgium, Brazil, Canada, Denmark, Finland, France, Germany, Hong Kong Japan, Netherlands, Norway, Poland, Portugal, Russian Federation, South Africa, Sweden, Turkey, the UK, and the US.

3 Available at: https://databank.worldbank.org/source/world-development-indicators/Type/TABLE/preview/on# (accessed on 07/25/2019).

Gross capital formation (constant 2010 US$) per labor force (GCF)	Gross capital formation consists of outlays on additions to the fixed assets of the economy plus net changes in the level of inventories. Fixed assets include land improvements (fences, ditches, drains, and so on); plant, machinery, and equipment purchases; and the construction of roads, railways, and the like, including schools, offices, hospitals, private residential dwellings, and commercial and industrial buildings. Inventories are stocks of goods held by firms to meet temporary or unexpected fluctuations in production or sales, and "work in progress." According to the 1993 SNA, net acquisitions of valuables are also considered capital formation.
CO2 emissions (kg per 2010 US$ of GDP) (CO2)	Carbon dioxide emissions are those stemming from the burning of fossil fuels and the manufacture of cement. They include carbon dioxide produced during consumption of solid, liquid, and gas fuels and gas flaring.
Renewable energy consumption (% of total final energy consumption)	Renewable energy consumption is the share of renewable energy in total final energy consumption.
Source: World Bank (2019).	

Table 2 provides descriptive statistics for all variables used in this study. There are considerable variations in indicators across countries. For example, GDP per capita ranges from a low of 5937.626 to a high of 91617.28. Moreover, R&D expenditure as a share of GDP ranges from a low of 0.46 to a high of 3.91.

Table 2: Summary Statistics

Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
GDP	340	37278.29	20011.41	5937.626	91617.28
RDE	332	1.893864	0.899704	0.46493	3.91382
TPA	340	53974.24	124773	146	605571
HTE	339	14.7954	7.385512	1.474043	35.80657
TLF	340	3.05E+07	3.84E+07	2404600	1.63E+08
GCF	340	16498.83	9116.238	2321.949	48155.44
CO2	300	0.354084	0.338906	0.083519	1.637187
REC	320	18.01201	16.18271	0.597432	60.18813

Notes: See Table 1 for the definition of variables. Obs, Std. Dev., Min, Max stand for observation, standard deviation, minimum and maximum, respectively.

Table 3 shows the correlations among the variables. We observed that there is a high correlation between RDE and GDP. A very high correlation is also observed between GCF and GDP. A high correlation between the independent variables may cause a multicollinearity problem in the regressions. Therefore, we chose to use one independent variable at a time and also to use all variables at the same time to see whether their explanatory powers changed due to the multicollinearity issue.

Table 3: Correlation Matrix.								
	GDP	**RDE**	**TPA**	**HTE**	**TLF**	**GCF**	**CO2**	**REC**
GDP	1							
RDE	0.7612	1						
TPA	0.0311	0.2225	1					
HTE	0.6638	0.6347	0.3983	1				
TLF	-0.3982	-0.0779	0.7880	0.0464	1			
GCF	0.9669	0.7105	-0.0309	0.5530	-0.4351	1		
CO2	-0.7476	-0.5299	0.1855	-0.4400	0.4197	-0.7374	1	
REC	0.0481	0.2098	-0.3018	-0.1896	-0.2116	0.0739	-0.2467	1
Notes: See Table 1 for the definition of variables.								

3.2. Modelling Strategy

The goal is to develop an empirical strategy that would enable us to explore the relation between technological innovation capacity and economic growth. The basic regression model that we aim to estimate can be expressed as follows:

$$GDPG_{i,t} = \beta_0 + \beta_1\ RDEG_{i,t} + \beta_2\ TPAG_{i,t} + \beta_3\ HTEG_{i,t} + \beta_4\ TLFG_{i,t} + \beta_5\ GCFG_{i,t}$$
$$+ \beta_6\ CO2G_{i,t} + \beta_7\ RECG_{i,t} + f_i + \epsilon_{i,t} \tag{4}$$

where $GDPG_{i,t}$ represents the real per capita GDP growth for country i in period t. $RDEG_{i,t}$ represents the logarithmic change in research and development expenditure, $TPAG_{i,t}$ represents the logarithmic change in total patent applications, $HTEG_{i,t}$ represents the logarithmic change in high-technology exports, $TLFG_{i,t}$ represents the logarithmic change in total labor force, $GCFG_{i,t}$ represents the logarithmic change of gross capital formation per labor force, $CO2G_{i,t}$ represents the logarithmic change in the CO2 emissions kg per GDP, and $RECG_{i,t}$ represents the logarithmic change in renewable energy consumption. f_i denotes country fixed effects, and $\epsilon_{i,t}$ is the usual error term. Our main parameters of interest are β_1, β_2 and β_3 which approximately describe the percentage change in economic growth as a response to one percentage increase in innovation measures. Country-fixed effects are included to control for any differences in the calculation of the variables and other unobserved time-invariant differences across countries.

This study uses panel data analysis in order to estimate the model. As Gujarati and Porter (2003) say, "panel data methods are used because they can provide 'more informative data, more variability, less collinearity among variables, more degrees of freedom and more efficiency." In the panel data model, f_i is called a "random effect" when it is treated as a random variable, and a "fixed effect" when it is treated as a parameter to be estimated for each cross section observation (Wooldridge, 2001). The term fixed effect means that one allows for arbitrary correlation between the unobserved effect f_i and the observed explanatory variables. Accordingly, f_i is called an "individual fixed effect." In the regression model, the zero conditional mean assumption - where the mean of the error terms given a specific value of the independent variable is zero is the necessary condition for consistent fixed effects and random effects estimations.

The regressions are estimated with the fixed-effects (FE) model since fixed-effects estimators are considered to be quite efficient in the case of panel data analysis. In order to see if it is safe to use fixed-effects, the analysis also includes the Hausman test indicating that, since the fixed-effects model is consistent when observed explanatory variables and unobserved effects are correlated, but random-effects (RE) model is inconsistent, a statistically significant difference is interpreted as evidence in favor of the fixed-effects model.

4. Empirical Results

In our panel model, we used real per capita GDP growth as the dependent variable in order to analyze the effects of explanatory variables on economic growth. Since our model is designed as a log-dif model, namely in logarithmic growth form, a possible data stationarity problem is eliminated. Therefore, the unit root test results are not reported in order to save space.

Table 4 provides the regression results obtained by using the OLS estimator as a benchmark model. According to the findings of the panel OLS regression, research and development expenditures, total patent applications and high-technology exports do not explain the long-run economic growth (Columns 1-4). As it can be seen from Table 4, total labor force growth and gross capital formation growth are positively and statistically significantly associated with economic growth while renewable energy consumption growth is negatively and statistically significantly associated with economic growth.

Table 4. Panel OLS Results (Dependent variable: GDPG)

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
RDEG	-0.008 (0.026)							0.015 (0.019)	0.016 (0.019)
TPAG		0.013 (0.012)						0.017* (0.009)	0.016* (0.009)
HTEG			-0.008 (0.012)					0.004 (0.009)	0.004 (0.009)
TLFG				0.217* (0.128)				0.234*** (0.089)	0.257*** (0.091)
GCFG					0.192*** (0.016)			0.199*** (0.016)	0.202*** (0.016)
CO2G						-0.025 (0.022)			-0.020 (0.018)
RECG							-0.035** (0.014)		-0.010 (0.011)
Constant	0.007 (0.006)	0.009*** (0.003)	0.008** (0.003)	0.007* (0.004)	0.010*** (0.002)	0.014*** (0.003)	0.008 (0.005)	0.007** (0.003)	0.012*** (0.003)
Observations	310	320	318	320	320	280	300	308	272
R-squared	0.467	0.470	0.469	0.474	0.709	0.493	0.485	0.730	0.749
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.

As we stated in Section 3.2, the OLS estimator is biased and inconsistent, though it provides a benchmark estimation for the coefficients, and therefore we focus on the results of the Fixed-Effects estimator, where the results are presented in Table 5. According to the FE test results, total patent applications growth is positively and statistically significantly associated with economic growth (Columns 2, 4 and 5). However, we did not observe any significant relationship between research and development expenditure and economic growth. On the other hand, total labor force growth and gross capital formation growth are positively correlated with economic growth. Other variables are statistically insignificant. The results did not change when we put all variables in the same regressions (Columns 8 and 9), ignoring the multicollinearity problem. Moreover, when we compared the estimated coefficients of the OLS and FE models, we observed that the magnitudes of the variables are smaller in the FE estimations, as expected.

Table 5. Fixed Effects (FE) Results.

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
RDEG	-0.032 (0.025)							0.008 (0.014)	-0.007 (0.017)
TPAG		0.012* (0.006)							0.015* (0.007)
HTEG			-0.011 (0.011)						0.004 (0.007)
TLFG				0.119* (0.065)				0.263** (0.097)	0.231** (0.086)
GCFG					0.176*** (0.018)			0.181*** (0.020)	0.180*** (0.018)
CO2G						-0.017 (0.015)			-0.005 (0.013)
RECG							-0.015 (0.015)		0.008 (0.011)
Constant	0.010** (0.004)	0.009** (0.004)	0.007 (0.004)	0.008* (0.004)	0.010*** (0.003)	0.010** (0.004)	0.010* (0.005)	0.008** (0.003)	0.006** (0.003)
Observations	310	320	318	320	320	280	300	310	272
R-squared	0.558	0.554	0.559	0.553	0.780	0.603	0.570	0.793	0.819
Number of Country	20	20	20	20	20	20	20	20	20
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.

The FE results indicate that if gross capital formation increases by 1%, it leads to a 0.17% increase in economic growth. Similarly, if total labor force increases by 1%, economic growth increases by 0.12%. Total patent applications have a positive but a smaller impact on economic growth. If patent applications increase by 1%, it leads to a 0.01% increase in economic growth. However, renewable energy consumption is not related with economic growth and this result supports the findings of Antonakakis et al. (2017). Moreover, renewable energy consumption is also not statistically significant based on the FE results and our finding is consistent with the existing empirical studies such as Irandoust (2016) and Antonakakis et al. (2017). Such results support the neutrality hypothesis which implies that energy is a relatively minor component of real GDP and thus it should have no significant impact on economic growth (Irandoust, 2016). From another point of view, based on Jevon's Paradox (1865), energy-efficiency improvements will increase rather than reduce energy consumption (Sorrell, 2009). An improvement in renewable energy technologies may lead an increase in total energy consumption and this may result in an increase in total expenditure on energy consumption. CO2 (kg per 2010 US$ of GDP) is also found statistically insignificant in both OLS and FE estimations. In all countries, CO2 emissions were declining during the observation period. It may be related with the innovations in renewable energy technologies that help to reduce CO2 emissions. Therefore, CO2 emissions may not be directly related to the GDP growth. High technology exports (% of manufactured exports) are also found statistically insignificant in our estimations. Apart from Belgium, France, Norway and Poland, the proportion of high technology exports in total manufactured exports was declining during the observation period.

Our findings on research and development expenditures are inconsistent with the relevant literature. These results may imply that the output of research and development activities could occur only in the long run and it could be in association with the economic growth in next periods but not today's economic growth. From another point of view, after the 2008 global financial crisis, in most of the countries in our sample, the increase in research and development expenditures was greater than the increase in GDP. This may result in an inverse relationship based on the findings of the model. Pack (1994) argued that the model proposing that R&D has an important effect on growth rates has not generated much confirmation in an economy-wide context (Griliches, 1988). Gross capital formation appears to be the most effective factor to explain economic growth based on the Fixed-Effects results. This result is consistent with both neoclassical growth theory and endogenous growth theory.

5. Concluding Remarks

This study explored the empirical link between technological innovation capacity and economic growth over the period between 2000 and 2016 for the panel of 20 developed and developing countries by utilizing the panel-type econometric models. Based on neoclassical and endogenous economic growth theories, in particular, we ask whether a number of indicators such as research and development expenditures, patent applications, high-technology exports and renewable energy consumption as the proxy of innovation play a role in the GDP formation for Austria, Belgium, Brazil, Canada, Denmark, Finland, France, Germany, Hong Kong, SAR-China, Japan, the Netherlands, Norway, Poland, Portugal, the Russian Federation, South Africa, Sweden, Turkey, the United States and the United Kingdom.

According to the results of the Fixed Effects model, total patent applications growth, total labor force growth and gross capital formation growth are statistically significant and positively correlated with economic growth. However, the findings of the current study do not support the previous research on research and development expenditure and economic growth nexus. On the contrary, our results support the neutrality hypothesis, which implies that energy is a relatively minor component of real GDP and thus it should have no significant impact on economic growth. As a policy suggestion, incentives for innovation and investments in R&D sector may support a sustainable growth in the long run. As innovation has profound effects on economy and it can lead to higher productivity, hence economic growth in the long run, the policymakers, even central banks, should be aware of its developments and research the economic and social preconditions that enable and support innovation.

Although our results did not provide a strong contribution of innovation capacity to economic growth we should keep in mind that the results might differ based on the selection of countries and the length of the time period. Future studies on the current topic are, therefore, recommended. In future investigations, it might be possible to use different proxies for technological innovations and a longer time period in order to test the endogenous growth theory.

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CHAPTER 3

ANALYSIS OF THE RELATIONSHIP BETWEEN R&D EXPENDITURE AND ECONOMIC GROWTH: COMPARISON BETWEEN DEVELOPING AND DEVELOPED COUNTRIES

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Abstract

In the global competitive environment, where international borders have been abolished and multilateral liberalization processes and economic cycles are experienced, a number of changes have occurred in the determinants of growth. Research and development activity (R&D) as an impulsive force of economic growth plays a leading role in the economic structures of countries. The R&D sector contributes to economic growth by creating externality via increasing returns in endogenous growth models. This study aims to test if the predictions of the R&D models are valid for developing and developed countries by using the annual data for the period 2000-2019. This study showed that R&D expenditures and the number of patents positively affected growth for both groups of countries.

Keywords: R&D Expenditures, Economic Growth, Panel Regression Analysis.

1. Introduction

Advances in science and technology have caused countries to undergo many changes in economic and social spheres. Technological developments have clear positive effects on critical matters such as streamlining human life, real income increase, productivity, increasing living standards, growth, and development. Technological advances manifest themselves as inventions and innovations created as a result of the studies depending on research and scientific knowledge (Capello & Lenzi, 2014).

One of the major challenges facing all countries regardless of their level of development is achieving sustainable economic development. Even though the factors that determine the economic growth performance of countries are wide-ranging, R&D expenditures, which constitute the fundamentals of technological progress, are thought to be a crucial determiner in terms of economic growth. The technological knowledge that is generated as a result of R&D activities permeates the whole economy and consequently, economic growth is actualized (Zerenler et al., 2007).

Looking at developed countries, it is seen that they proceed with an innovative perspective and concentrate on the infrastructure and the R&D activities required for innovation. Therefore, it is possible to note that these factors create positive effects for the countries in attaining the status of being a developed country. In the statistical indicators of these countries, the share of R&D expenditures in GDP is observed to be high. This situation confirms the hypothesis that high R&D expenditures in developed countries will produce a growth-enhancing effect. In developing countries, the infrastructure and R&D activities required for innovation are at low levels; therefore the outputs are not on a grand scale. The way for developing countries to finally become "developed" is to create a difference in the global competitive environment by presenting new products and new production methods to new markets. Developing countries can create economic value only through R&D and innovation. It is the developing countries in particular, which need to put much more emphasis on R&D and innovation in order to solve their economic problems (Karakaş & Adak, 2014). Developing countries have always been in search of ways of increasing their welfare levels. However, the different approaches adopted in these searches have been reflected in their development levels. With globalization, innovation and R&D have become concepts that determine the development levels of societies.

This study aims to analyze the impact of R&D expenditure on growth in both developing and developed countries by using panel regression analysis with data obtained from the period 2000-2019 and make comparative comments.

2. The Importance Of R&D Expenditures For Countries

Innovation plays an important role in increasing the production, quantity, and quality of products and services, and in the emergence of new branches of industry and new business opportunities. It has a direct impact on the growth of the economy and increasing social welfare. It helps to increase the economic resources and quality of life of individuals. Therefore innovation is both economically and socially important. A novelty introduced by a company contributes to the development of new products and production processes by creating a stimulating effect first in the relevant industry and then in the whole economy. The innovation resulting from an investment in an invention creates a "technological multiplier" effect and helps other companies to accomplish a range of novelties. R&D studies are essential in terms of ensuring the efficient, planned, and rational use of the resources available in countries. Moreover, R&D studies contribute to finding solutions to the economic and social problems of countries and to investigating their causes (Uzun Kocamış & Güngör, 2014).

New companies play an effective role in realizing technology transfer between sectors by assisting the transformation of knowledge into technological products. Therefore, the increase in R&D studies and R&D return rates will create a positive effect on technology exports and dependence on foreign sources will be diminished (Atkinson & Ezell, 2012). The increase in R&D activities helps to increase and diversify economic efficiency by enabling regional and local restructuring of the economy. The development of R&D activities creates economic value and accelerates the emergence of innovative companies. Thus, it helps to groom new entrepreneurs and to increase employment areas. Moreover, the emergence of new employment areas assists in the prevention of brain drain as well. In this respect, R&D helps to increase the welfare levels of countries by facilitating the efficient use of economic resources. All these factors, which are targeted with R&D expenditures, play an active role in increasing the competitiveness levels of countries (Yaylalı et al., 2010).

Countries have different social, political, and economic characteristics and these will affect the capacity of R&D investments to contribute to innovation and growth. Thus there are some countries that can transfer most of their R&D expenditure to innovation and economic growth, while there are others that cannot manage to transfer R&D expenditure to innovation and growth to the same degree. Education level, unemployment, demographic characteristics, as well as investment volume, are factors affecting societies because science and technological knowledge require a good education, long-term experience, and talent. The economic conditions of the country, on the other hand, will reflect the number of resources allocated to R&D investments and the extent of sectoral development (Bilbao-Osorio & Rodriguez-Peso, 2004). R&D expenditures make positive contributions to economic growth by creating a set of advantages in economic activities. These advantages are:

1- **Competitive Advantage:** The most important factor which determines the competitiveness of a country in the international arena is technological developments, hence, R&D expenditures.
2- **Attracting Foreign Capital:** The technological prowess of a country is highly essential in attracting foreign direct investments to the country and for foreign companies to make technology-oriented investments in the country.
3- **Productivity Increase:** R&D expenditures are key factors in promoting economic development by increasing productivity at the micro and macro levels. For example, due to the knowledge or technology created as a result of R&D expenditures, problems will be solved in areas such as environment, health, and economy, resulting in positive contributions to humanity.
4- **Eliminating Technological Dependence:** R&D expenditures save countries from being dependent on other countries in terms of technology (Inekwe, 2015).

R&D activities make a substantial contribution not only to the increase in production and economic performance but also to the accomplishment of social objectives. Based on these aforementioned advantages and functions of R&D expenditures, it can be said that they are the most important factors to be considered when measuring the development level of a country. For developing countries to compete in the world market and maintain their industrial assets, they need to acquire competence in technological innovation and base their competence in their R&D. Although the science is international to a certain extent, developing technology and creating R&D awareness are national concepts. As a measure of the emphasis on science and technology and development level in a country, the share of resources allocated to R&D expenditures in GDP is taken into account. If any country's ratio of R&D expenditures in its GDP is more than 2 percent, those countries are considered to be developed countries. Although technological development has gained a global dimension, technological developments are monopolized by about a mere 15-20 developed countries. These countries account for 95 percent of the R&D expenditures in the world. On the other hand, developing countries, which constitute about 70% of the world's population, make only 5 percent of total R&D expenditures (Silaghi et al., 2014).Another R&D indicator is related to R&D financing. In developing countries, R&D financing is provided by the public sector, while in developed countries this funding is provided by the private sector. While 55-70% of R&D financing is provided by the private sector in developed countries, this rate is below 50% in developing countries. Another indicator of the comparison of international R&D structure is the R&D personnel employed in the R&D sector.

Unless underdeveloped and developing countries launch intensive efforts to develop or transfer technology, the divergence between countries will continue, and these countries will not be able to converge with developed countries. The differences of technology, cost, productivity, and competitive power between developed countries and underdeveloped or developing countries are caused by insufficiencies in technological development and innovation activities, human capital and infrastructure deficiencies, financing problems, institutional and structural problems, and macroeconomic instabilities (Kılıç et al., 2011).

Moreover, the European Union has decided to formulate a new strategy to cope with the problems arising due to recent crises, intense competition, and issues emerging accordingly, with a holistic approach on behalf of unity. Within the framework of this strategy, which was announced by the European Commission in 2010, the main priorities for the purpose of establishing high employment, productivity and social cohesion are defined as follows:

- **Smart Growth:** Developing the economy based on knowledge and innovation,
- **Sustainable Growth:** Promoting a greener and more competitive economy, where resources are used effectively,
- **Inclusive Growth:** Achieving high levels of employment to ensure social and regional cohesion. The objective is to achieve the goal of allocating 3% of the GDP to R&D, to improve conditions for the private sector to invest in R&D, and to create a new indicator for monitoring innovation (Akbaş & Apar, 2010).

Economic progress and development in an economy of free markets can only be possible by producing goods and services which can penetrate international markets. Companies that tend to overlook technology investments inherent to their industry will inevitably lose their competitiveness and have to withdraw from their market. Therefore, it is inevitable for companies to attach importance to R&D. According to OECD data, more than half of the recent growth in developed economies is driven by innovation. Nowadays, the comparative advantage based on capital and natural resources has now been replaced by superiority in information and technology (Göçer, 2013).

3. Literature Review

The intensity and direction of the relationship between R&D and economic growth vary according to the economic structure of a country. The literature on the relationship between R&D and economic growth is dominated by the view that R&D expenditures support economic growth. However, the scale at which R&D expenditures can support economic growth is significantly affected by the efficiency of expenditures and the internal dynamics of the national economy.

Table 1. The literature on the relationship between R&D expenditures and economic growth.

Sylwester (2001)	20 OECD countries 1980-2000	It was concluded that there is no relationship between R&D spending and economic growth and that there is a positive relationship between industrial R&D spending and growth in the G7 countries.
Bassanini & Scarpetta (2001)	21 countries 1970-1980 and 1980-1990	They determined that a 1% increase in R&D spending increased economic growth by 0.4%.
Guellec & Van Pottelsberghe (2004)	16 OECD countries 1980-1998	They found that R&D activities are a significant determinant of the increase in productivity in the long run.
Ülkü (2004)	30 countries 1981-1997	It was concluded that there is a positive relationship between the number of patents created by the R&D sector and GDP per capita.
Zachariadis (2004)	10 OECD countries 1971-1995	It was concluded that the increase in R&D expenditures positively affected the growth rate.
Falk (2007)	15 OECD countries 1970-2004	It was concluded that R&D expenditures and the increase in high technology R&D investments had a strong and positive effect on both GDP per capita and GDP per worker.
Wang (2007)	30 countries 2000-2006	They determined that countries that use R&D expenditures effectively will have better economic performance.
Özer & Çiftçi (2008)	OECD countries 1990-2005	They determined that R&D expenditures have a positive and significant impact on GDP.
Saraç (2009)	10 OECD countries 1983-2004	It was determined that R&D expenditures have a positive impact on economic growth.
Samimi & Alerasoul (2009)	30 countries 2000-2006	They determined that R&D investments do not affect economic growth, as developing countries devote few resources to R&D activities.
Alene (2010)	52 countries 1970-2004	It determined that a 1% increase in agricultural R&D expenditures would increase total productivity by about 0.20%.
Genç & Atasoy (2010)	34 countries 1997-2008	They determined that there is a causality relationship between R&D expenditures and economic growth.

Horvath (2011)	72 countries 1960-1992	It determined that R&D expenditures have a positive impact on long-term growth.
Güloğlu & Tekin (2012)	13 countries 1991-2007	They determined that there is bi-directional causation between technological innovation and economic growth.
Kirankabeş & Erçakar (2012)	31 countries 1997-2007	They determined that there was a significant positive relationship between R&D expenditures and patent number and growth.
Eid (2012)	17 countries 1981-2006	This study found that R&D expenditures had a significant and positive effect on the increase in productivity after the year in which they were made.
Gülmez &Yardımcıoğlu (2012)	21 OECD countries 1990-2010	They found that there is a long-term bi-directional causality relationship between R&D expenditures and economic growth and that a 1% increase in R&D expenditures increases economic growth by 0.77%.
Göçer (2013)	11 countries 1996-2012	The 1% increase in R&D expenditures supported exports of high-tech products by 6.5%, exports of information and communication technologies by 0.6% and economic growth by 0.43%.
Doruk & Söylemezoğlu (2014)	22 developing country 2000-2007	R&D expenditures have positive effects on economic growth.
Özcan & Arı (2014)	15 OECD countries 1990-2011	It was concluded that R&D expenditures have a positive impact on economic growth.
Bozkurt (2015)	Turkey 1998-2013	There was a one-way causality from GDP to R&D expenditures, but no causality from R&D to GDP.
Bilas et al. (2016)	EU countries 2003-2013	There is a causality relationship between R&D expenditure and economic growth.
Blanco et. al. (2016)	USA 1963-2007	R&D investment has a positive effect on economic growth.

4. Econometric Analysis

4.1. Data

In the study, 10 developed countries and 10 developing countries were analyzed for the period between 2000 and 2019. A panel regression model was analyzed to determine the relationship between the independent variable, i.e. the ratio of R&D expenditures to GDP (R&D) and the dependent variable, i.e. growth (GRW). In addition, the number of patents (PATS) was included in the model as the control variable. The data were obtained from www.worldbank.org. Developed countries composing the sample of the study are Norway, Germany, the United Kingdom, France, Belgium, Austria, Canada, Finland, Switzerland, and Denmark. Developing countries are Turkey, Bulgaria, Romania, Malaysia, Russia, Mexico, Brazil, South Africa, Poland, and India.

4.2. Testing Homogeneity and Cross-Sectional Dependence

First-generation unit root tests are categorized into two as homogeneous and heterogeneous models. Levin, Lin, & Chu (2002), Breitung (2005), and Hadri (2000) tests are based on the homogeneous model assumption, while Im, Pesaran, & Shin (2003), Maddala & Wu (1999), and Choi (2001) tests are based on the heterogeneous model assumption. In this study, relationships will be determined using regression analysis. However, cointegration analysis was not to be performed since the efficiency and reliability of the unit root test to be used would vary according to the presence of heterogeneity and cross-sectional dependence, but both homogeneity and cross-sectional dependence were tested to determine the suitable test.

Table 2. Paseran and Yamagata (2008) homogeneity test results.

Developed countries			Developing countries		
	Test statistics	**p**		**Test statistics**	**p**
$\tilde{\Delta}$	9.463	0.000*	$\tilde{\Delta}$	11.890	0.000*
$\tilde{\Delta}_{adj}$	10.356	0.002*	$\tilde{\Delta}_{adj}$	10.342	0.006*

* Significance at 0.05 level.

As the probability values of the tests calculated in Table 2 were less than 0.05 for both country groups, H_0 was rejected. It was decided that the slope coefficients were not homogeneous. The first-generation Im, Pesaran & Shin (2003), Maddala & Wu (1999) and Choi (2001) tests, which were based on the assumption of heterogeneity, were used in the study. First-generation unit root tests are based on the assumption that the cross-sectional units forming the panel are independent and that all the cross-sectional units are equally affected by a shock that occurs to one of the units forming the panel. However, it is a more realistic approach that a shock to a cross-sectional unit which constitutes the panel would affect other units at different levels. In order to overcome this deficiency, second-generation unit root tests were developed to analyze stationarity by taking into account the interdependence between the cross-sectional units.

When panel data is used to test for the presence of a unit root, the cross-sectional dependence must then be tested. If the cross-sectional dependence is rejected in the panel data set, then, 1st generation unit root tests can be used. However, if there is a cross-sectional dependence in the panel data, using 2nd generation unit root tests will provide a more consistent, effective and strong estimation.

The cross-sectional dependence between the series was determined using the LM CD test developed by Pesaran (2004) and the LM adj. test, of which the deviation was corrected by Pesaran et al. (2008), and test results are presented in Table 3. Since the probability values of the test results were less than 1% and 5%, the null hypothesis (no cross-sectional dependence) was rejected and cross-sectional dependence was determined to exist between the series.

Table 3. Cross-sectional dependence test results.

Cross-sectional dependence test (H_0: no cross-sectional dependence)		
Developed countries		
Test	**Test statistics**	**p**
LM (Breusch and Pagan (1980)	15.982	0.000*
LM $_{adj}$ (Pesaran et al. (2008)	22.364	0.000*
LM CD (Pesaran (2004)	19.622	0.003*
Developing countries		
Test	**Test statistics**	**p**
LM (Breusch and Pagan (1980)	10.731	0.000*
LM $_{adj}$ (Pesaran et al. (2008)	11.099	0.000*
LM CD (Pesaran (2004)	12.534	0.021*
* Significance at 0.05 level.		

Since the probability values of the test results were less than 1% and 5%, the null hypothesis (no cross-sectional dependence) was rejected and cross-sectional dependence was determined to exist between the series. In this case, there is cross-sectional dependence among the countries which constitute the panel. The shock to one country affects the others.

4.3. Unit Root Tests

4.3.1. First-Generation Unit Root Tests Results

In Table 4, the t-value and probability values at the level and first-order differences resulting from the application of 1st-generation unit root tests to panel data as constant + trend are given separately.

Table 4. First-generation unit root tests

Country group	**Variables**		**Im, Pesaran, & Shin (2003)**	**Maddala & Wu (1999)**	**Choi (2001)**
Developed countries	R&D	Level	-1.109(0.172)	5.966 (0.101)	-0.877(0.214)
		∇	-6.933(0.001)*	34.993(0.000)*	-6.990(0.000)*
	GRW	Level	-0.821(0.149)	8.251(0.250)	-1.045(0.231)
		∇	-7.886(0.001)*	37.369(0.000)*	-11.903(0.000)*
	PATS	Level	-0.923(0.251)	8.225(0.259)	-0.887(0.132)
		∇	8.451(0.000)*	39.441(0.000)*	-9.561(0.001)*
Developing countries	R&D	Level	-0.863(0.138)	7.611(0.150)	-0.913(0.149)
		∇	-6.790(0.000)*	39.903(0.000)*	-11.273(0.000)*
	GRW	Level	-0.822(0.173)	8.405(0.281)	-1.142(0.237)
		∇	-7.653(0.001)*	39.044(0.001)*	-9.962(0.002)*
	PATS	Level	-1.055(0.178)	8.463(0.205)	-0.901(0.124)
		∇	-7.563(0.000)*	38.559(0.000)*	-8.364(0.000)*

Note: ∇ represents the first-order difference, *indicates the stationary state. The deterministic specification of the tests includes constant and trend. Probability values are indicated in parentheses. Tests were made for significance at 5% level. The zero hypothesis of the tests is that the unit has a root. The optimal lag length was determined using the Schwarz information criterion.

As seen in Table 4, all variables have unit roots in their level values. However, the first difference series do not contain a unit root. Therefore, it can be observed that all variables are I(1), in other words, they are stationary for the first-order difference.

4.3.2. Second Generation Unit Root Test Results

In this study, the stationarity of the series was tested with CADF, which is a second-generation unit root test, since cross-sectional dependence was determined between the countries that compose the panel. In the CADF test, it was assumed that the error term consists of two parts as common to all series and specific to each series. In this model, it was assumed that cross-sectional dependence was due to the presence of an unobservable common element. The hypotheses of the test are as follows;

H_0: Has a unit root

$H_{1:}$ Has no unit root

For this test, the CADF statistics for each country are calculated first. These calculated values are then compared with the table values calculated by Pesaran (2006) using the Monte Carlo simulation. To determine the presence of unit root throughout the panel, the arithmetic average of the CADF statistics found for each country are taken and CIPS statistics are calculated. The calculated CIPS statistics are compared with the table values in the study of Pesaran (2007). If the resulting CIPS value is less than the critical value of the table then H_0 is rejected. CIPS statistics were calculated, and the results obtained are presented in Table 5.

Table 5. CIPS test results.

Country group	Variables	CIPS statistics
Developed countries	R&D	-7.452*
	GRW	-9.881*
	PATS	-8.471*
Developing countries	R&D	-8.809*
	GRW	-9.637*
	PATS	-9.334*

*Stationary series for first-order difference
Note: For CIPS Pesaran (2007) p 281 In Table IIc, the critical value at 5% significance level = -2.922. The number of lag was determined according to the Schwarz Information Criteria. Trend + constant model was studied.

Since the calculated CIPS statistic was greater than the table critical value, H_0 was accepted, and it was concluded that there was no unit root when the first-order difference was taken in the series composing the panel. In this case, the series were not stationary in the level values; they were stationary when the first-order difference was taken. Since the series were not stationary in the level values, regression analysis was performed with the first-order differences.

4.4. Findings and Comments on the Panel Regression Analysis

Panel data methods are performed with pooled, fixed and random effects as stated in the study by Baltagi (2005). In this research, some statistical tests are performed in order to choose between two possible estimation models. Since all variables in the models can vary between countries and times, the basic question is whether to collect the data between countries and times (pool data). Table 6 shows the results of Chow and Breusch-Pagan (BP) tests that were applied to determine which panel regression model to choose. While the H_0 hypothesis for the Chow test was pooled regression and H_1 hypothesis was the fixed effects model (FEM), the Ho hypothesis in the BP test was considered as pooled regression and H_1 as a random-effects model (REM).

Table 6. Panel regression estimation method selection test results for country groups.

Developed countries				**Developing countries**		
Test	**p**	**Decision**		**Test**	**p**	**Decision**
Chow(F test)	0.001	H_1 accepted		**Chow(F test)**	0.001	H_1 accepted
BP(χ^2 test)	0.018	H_1 accepted		**BP(χ^2 test)**	0.003	H_1 accepted
Hausman test	**Cross-section random**		0.195	**Cross-section random**		0.185
	Period random		0.167	**Period random**		0.171
	Cross-section and period random		0.132	**Cross-section and period random**		0.158

The other stage consists of using the Hausman test to test hypotheses of H_0: Random effect (REM) and H_1: Fixed effect (FEM). As can be seen from the test results, the H_0 hypothesis was accepted for both countries and the REM model was decided upon. Different algorithms were tried for the analysis. The model estimation results that were obtained for developing countries by the Cross-section SUR algorithm giving the smallest total error square and the results for developed countries by the White Cross-section method were analyzed by taking the first-order difference of the variables; the results are presented in Table 7.

Table 7. Results of panel regression estimation for country groups

Panel Regression Estimation Results for Developing Countries

Dependent variable: **D(GRW)**
Method: Cross-Section SUR (PCSE)

	Coefficient	**Std. error**	**t-statistic**	**p**
D(R&D)	0.057	0.014	4.071	0.000*
D(PATS)	0.072	0.025	2.889	0.028*
C	2.128	0.503	4.230	0.000*

R^2 = 0.561 $F_{statistic}$ = 27.31 F(p)= 0.000 DW=1.993
Wooldridge autocorrelation Test (p)=0.125
Greene Heteroscedasticity Test (p)=0.178

Panel Regression Estimation Results for Developed Countries

Dependent variable: **D(GRW)**
Method: White Cross-Section

	Coefficient	**Std. Error**	**t-statistic**	**p**
D(R&D)	0.115	0.012	9.583	0.000*
D(PATS)	0.092	0.026	3.538	0.001*
C	3.851	0.483	7.973	0.000*

R^2 = 0.602 $F_{statistic}$ = 29.66 F(p)= 0.000 DW=2.104
Wooldridge autocorrelation Test (p)=0.193
Greene Heteroscedasticity Test (p)=0.245
*Significant variable at 0.05 level

When Table 7 is reviewed, it can be seen that R&D and PATS variables have significant positive effects on the GRW variable for developed and developing country groups. When the coefficient values were analyzed, it was determined that the effect of the R&D variable on GRW in developed countries is twice as high as in developing countries. This situation reveals a very important difference.As a result of the hypothesis tests of the model for both country groups, it was determined that there were no autocorrelation and heteroscedasticity problems. As a result of the F test, the models were found to be significant.

5. Conclusion

As a result of structural changes in their economies, countries consistently increase their production, as well as the utilization of information. Today, developed countries, that create big differences in science and technology and are at the forefront of competition, allocate the largest share in their GDPs to R&D and innovation. It is of great importance for developing countries to generate technological knowledge through R&D and innovation, to increase product quality and standards, to reduce production costs, and to make their economies competitive on an international level.

In this study, 10 developed countries and 10 developing countries were taken as examples for the period between 2000 and 2019. A panel regression model was analyzed to determine the relationship of the independent variable, i.e. the ratio of R&D expenditures to GDP (R&D) and the control variable, i.e. the number of patents (PATS) with the dependent variable, i.e. growth (GRW). As a result of the analysis, it was determined that R&D and PATS variables had a significant positive effect on the GRW variable for both country groups. The effect of these two variables is two times higher for developed countries than for developing countries. Significant differences were determined between the two country groups. This confirms the hypothesis that high R&D expenditures in developed countries will help to increase growth. In developing countries, the infrastructure and R&D activities required for innovation are at low levels; therefore, the outputs are not of a grand scale.

Developing countries need to increase their due growth performance to catch up with developed countries and opt for long-term R&D investments rather than short-term solutions in order to make this performance sustainable. It should be emphasized that they should allocate more shares to R&D expenditures from their national income and make educational arrangements for training a highly skilled labor force that will realize advanced technology production. Not only the government but also the private sector should attach importance to R&D investment in the long run in order to survive and grow in globalizing and ever-growing world markets.

As a result of the study, it can be affirmed that technological innovations and existing knowledge stock can be created through R&D activities and that technological knowledge will consistently increase the economic growth rate by providing new investment and an increase in employment opportunities. It should be kept in mind that innovations created with technological knowledge will enable the increase of both physical capital and human capital and will prevent decreasing yields, therefore sustaining economic growth. It would be beneficial for developing countries to determine reliable technological progress strategies, prepare necessary institutional and physical infrastructures for this purpose, allocate more of their national incomes to R&D activities, improve their human capitals and industrial infrastructures to produce high-tech products, and provide incentives to foreign investors who can transfer technology to their countries. In these countries, establishing R&D centers and building facilities for technology development and commercialization of these technologies will positively contribute to technological progress. It may be beneficial to provide R&D investments with tax exemptions and infrastructure support to enable the private sector to have a more active role in the technology development process. The cooperation, coordination, and mutual knowledge sharing between the public and private sectors in R&D activities should be ensured, and the share of the private sector in R&D activities should be increased as much as possible.

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CHAPTER 4

A PANEL COINTEGRATION STUDY OF THE EFFECT OF R&D EXPENDITURES ON INNOVATION: THE CASE OF BRICS_T COUNTRIES

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Abstract

In academic and intellectual discussions on how to achieve sustainable growth and development in the world, it is stated that it is not easy for countries to gain, develop and maintain competitiveness in the globalization environment and often noted that it will not be possible without Research and Development (R&D) and innovation activities. In this context, this study examines the relationship between R&D expenditures to GDP ratio and global innovation index in the scope of BRICS_T countries (Brazil, Russia, India, China, South Africa, and Turkey). For this, panel cointegration and causality analyses were applied based on data covering the period 2007-2019. First, horizontal cross-sectional dependence between series was analyzed by the LM CD test developed by Pesaran (2004) and LM adj. test whose deviation was corrected by Pesaran et al. (2008). After cointegration coefficients were determined as heterogeneous, 1st and 2nd generation unit root tests were implemented. 1st generation unit root tests Maddala & Wu (1999), Choi (2001), and Im, Pesaran & Shin (2003) were applied; stationarity was tested by CADF test, one of the 2nd generation unit root tests; Westerlund & Edgerton's (2007) LM Bootstrap Panel Cointegration test was utilized for detecting long-run relationship between variables. After long-run coefficient estimations were performed through FMOLS, Dumitrescu & Hurlin (2012) causality test was applied. Consequently, the statistically significant positive effect of R&D on global innovation index GII was determined. The highest effect was in China and Russia. Panel-wide, a 4.3% enhancing effect was determined. In addition, two-way causality was detected between the R&D and GII variables.

Keywords: BRICS_T Countries, Research and Development, Innovation, Innovation Index.

1. Theoretical Background

There is an outward shift in the production possibility frontier (PPF) of the whole economy, which is one of the reasons for the economy's long-term development (Hale, Kahui, and Farhat, 2015). In terms of 'innovation', it can be said that this is one of the factors that will lead to a shift in the production possibility curve of the economy (Aghion, et al., 2018). Therefore, there must be an existence of R&D expenditures in the development of innovative services and products. According to Luthar (2015), investment policies for R&D teams are required for creating an incentive for innovation which will lead to the materialized form thereof. It will help transform the proceeds into the process of the economy using investment (King, 2015). Therefore, in the absence of private and the public expenditure on the research and development activities, the maximum of innovations cannot be implemented, and the productivity of the economy will not be feasible (Sauvé, Bernard & Sloan, 2016).

1.1. Innovation

It seems best to analyze the history of the word in order to appreciate the notion of innovation. The concept of innovation, derived from the Latin word 'innovatus', has been discussed in its development dimension by Mees (1920) and Holland (1928) and in its financial dimension by Mauclaurin (1953) and Enos (1962). As Grovers (1974, p. 4) emphasized, in the context of public finance rooted in economics, the concept of innovation, which is especially important in terms of public policies and the effectiveness thereof, was accepted by Fischer (2001, p. 200) as the basis for achieving economic prosperity by ensuring sustainable competition; it was stated that the perception of innovation merely as R&D activities would reflect a very shallow point of view; and the concept of innovation was considered as a concept covering technical revolution, managerial revolution and development processes.

Again, in Chapter 12 entitled Crumbling Wall in *Capitalism, Socialism, and Democracy,* written by the economist and political scientist Schumpeter, the concept was explained as follows by means of including the expression of innovation itself: Nowadays, it is far simpler to perform anything apart from everyday routine. Unlike in the past, innovation itself has been reduced to a routine. Technological advancement is progressively becoming the work of the qualified professional teams who produce what is needed and make them operate in expected ways (Schumpeter, 2003, p.133). As can be understood from these explanations, innovation has been used as a concept referring to previous ways of business manners, changes that occur in business models and, technological advances.

The Oslo Manual by the Organization for Economic Co-operation and Development (OECD) provides the following information on innovation (OECD, 2005): The innovation concept is characterized as follows: Innovation is connected to uncertainty regarding the results of innovation operations. It includes investment, is likely to be affected by spillovers, requires either the utilization of new knowledge or a modern application or blending of the present knowledge, and aims to raise the efficiency of a company by means of obtaining a competitive advantage.

The document focusing on the measurement of innovation describes four types of innovation: Product innovation: A product or service that is original or remarkably upgraded. This involves important enhancements to technical requirements, parts and materials, product software, usability, and other functional features. Process innovation: A novel or considerably enhanced method of manufacturing or distribution. This involves substantial modification in the techniques, equipment, and/or software. Marketing innovation: A unique marketing technique suggesting important modifications in the design or packaging of products, product placement, product promotion or pricing. Organizational innovation: A novel organizational approach for business practices, organization of the workplace or external relations. Economists suppose that organizational change is a reaction to technical change. However, in point of fact, organizational innovation might be a prerequisite for technical innovation.

Furthermore, Godin (2008) stated that the history of innovation as "creativity" is comprised of three notions (plus their derivatives): Imitation leads to Invention and Invention leads to Innovation. There is a great deal of literature about imitation (theories of literature and art) besides invention (sociology, history, management, and technological economics). In this context, innovation is expected to create economic value, unlike invention. An invention is the beginning process of innovation, and it is necessary to study and develop it in a different way for it to be able to transform into a product/service that adds value to the market. Invention emerges as a result of R&D processes. For the development of R&D, the scientific/academic base of a country needs to develop. Essentially, the process can be expressed in the following order: Science/Academy, R&D, Invention/Patent, Innovation, Economic Growth/Welfare (Tiryaki, 2014).

Innovation is usually recognized as a major factor that enables countries to promote their economic growth and competition power. Therefore, embracing current technologies effectively and efficiently is a major means of continuing economic growth and development (Hu, 2015; Huggins et al., 2015).

As can be seen, compared to R&D activities, innovation is more comprehensive, involving advancements in logistics, support and sales/marketing efforts. Besides, the scope of innovation also covers the procurement of external know-how or industrial goods, which lies beyond the scope of R&D generally. The innovative actions which companies decide to engage in depend on their access to technology, information, and knowledge, as well as to financial and human resources. For the said reasons, it is better to take a closer look at R&D, which is an important component of innovation.

1.2. Research and Development (R&D)

R&D, which is one of the most important stages of innovation and is indeed a prerequisite thereto, helps innovation to emerge technically. However, it is useful to take a look at the concept of the research partnership in order to mention an effective R&D activity. Partnerships are described as cooperative arrangements that gather up businesses, universities, government agencies, and laboratories into several alliances to combine resources to achieve a mutual R&D goal (The Council on Competitiveness, 1996). Within this context, the concept of research partnership is expressed by Hagedoorn et al. (2000) as follows: in general, a research partnership is a connection that is based on innovation that requires major endeavor, at least in part, in research and development (R&D).

Bilbao & Rodriguez (2004) indicate that the fact that investment in R&D improves the chance of attaining higher technological standards in companies and countries enables them to implement new and better goods and/or procedures, leading to higher rates of revenue and growth. According to Samimi & Alerasoul (2009), R&D is the key to productivity and economic growth. Likewise, Kim (2011) indicates that doing and learning are the two principal functions of R&D activities. The transfer of knowledge, in this phase, is denoted as the “spillover effect”. Innovation arises by means of knowledge, thus, manufacturers can present unique products, decrease expenses, and enhance product quality. R&D is, therefore, strongly associated with productivity.

R&D activities are defined by OECD (2015) as follows: Research and experimental development (R&D) comprises of an inventive and methodical activity that is initiated in order to boost the stock of knowledge and develop novel practices for existing knowledge. R&D activities must meet five core criteria, which are novelty, creativity, uncertainty, systematicity, transferability, and/or reproducibility. Besides, R&D activities are classified into 3 different groups: These are Basic Research, Applied Research, and Experimental Development. Basic research is an empirical or theoretical study that investigates new knowledge on the fundamental basis of phenomena and observable evidence, regardless of considering any specific application or usage. The second, Applied Research, is original research which is conducted to pursue a particular practical purpose or objective. Finally, Experimental Development is a methodical study that utilizes the knowledge acquired from exploration and applied experimentation with the purpose of creating new products or procedures or upgrading current products or procedures. The R&D system contains numerous flows of data and knowledge. Experimental development can provide data for basic research, and it is also possible that basic research can immediately result in new products or procedures. Furthermore, R&D Classification is specified to include the following fields: Natural sciences (Mathematics, physical sciences, computer & information sciences, etc.); Engineering & technology (Electrical engineering, information engineering, electronics, etc.); Medical & health sciences; Agricultural & veterinary sciences; Social sciences (Economics & business, political sciences, etc.); and Humanities & the arts.

Additionally, the Law on Supporting Research and Development Activities dated 28.02.2008 and numbered 5746, and the Law on Technology Development Zones dated 26.06.2001 and numbered 4691 are both principal codes regulating incentives intended for research and development projects in the financial sector of Turkey. From this perspective, the R&D definition is as follows. Research and development activity (R&D): Research and development refers to original work carried out on a methodical foundation, to improve the bank of knowledge made up of the knowledge of culture, people and society, and to use that knowledge to design new processes, systems, and applications; activities that provide scientific and technological development in their area through environmentally compatible product design or software projects, focusing on scientific and technological uncertainty, and whose outputs have original, experimental, scientific, and technical content.

According to the Regulation on Application and Control for Supporting Research, Development and Design Activities published in the Official Gazette dated 10.08.2016 and numbered 29797: The activities which are not evaluated within the scope of R&D and innovation activities are as follows:

a) Marketing activities, market monitoring processes, marketing surveys or promotional sales programs
b) Quality control
c) Studies carried out in the field of social sciences
d) Search and drilling exercises for petroleum, natural gas, and mineral reserves,

e) The clinical studies of which at least two stages have not been performed domestically before a drug manufacturing license; and the clinical studies which are carried out after obtaining a manufacturing license,

f) Utilization of procedures devised outside the extent of an R&D plan or usage of existing improved procedures,

g) Stylistic variances involving aesthetic and visual changes in shape, color, decoration and the like, which are not intended for R&D and innovation activities,

h) Software development exercises performed by utilizing existing software to help in the preparation of websites and the like, excluding instruction codes and operating systems,

ı) Software-related regular and repeated actions, which do not involve scientific or technological advances or the resolution of technological uncertainties,

j) Research-related expenditures of enterprises and organizations

k) Expenditures on investment projects intended for production and production substructure, projection of commercial manufacturing and mass production process,

l) Duplicating and distributing copies from prototypes for providing samples, and consumer tests for advertising purposes,

m) Transferring technology directly or in an embedded form, which does not subserve the presentation of a novel procedure, system or product without being a part of an R&D project,

n) Activities for the protection of intellectual property rights, except for the acquisition of the said rights relating to a product or procedure designed by means of R&D and innovation projects.

2. Literature Review

In his study, Falk (2000) analyzed the impacts of R&D spending on economic growth among member nations of the OECD through panel data analysis based on the data from 1970 to 2004. The results show that both the ratio of corporate R&D spendings to GDP and the percentage of R&D investments in the cutting-edge high technology sectors have powerful positive impacts on both per capita income and average per capita hourly earnings in the long run. Segerstrom (2000) examined the impacts of R&D incentives on long-run growth. The result of this study was significant and showed that R&D incentives either promote or postpone the long-run economic growth. The result where the growth is delayed depends on a range of reasonable parameter values. This research also presents a fresh view on why R&D subsidies have an impact (both positive and negative) on long-term financial development.

Coe et al. (2008) concluded that organizational differences are important determinants in terms of total factor productivity and that its grade is impacted by R&D spillover. Kim (2009) examined the impact of R&D operations on Korea's economic growth using the data for the period 1976-2009, via Cobb-Douglas' R&D-based production function. As a result, the experimental findings of the study present that the conventional factors of production (labor and capital) contribute to economic growth by almost 65%. Furthermore, R&D stocks contribute to economic growth by about 35%. When reviewed in detail, it can be observed that private and public R&D stocks contribute to economic growth approximately by 16% and 19%, respectively.

Nunes et al. (2012) performed an analysis to discover if there was a comparable connection between small and medium-sized businesses with leading-edge technology and those without, with regards to R&D intensity and growth. The findings show that concentration on R&D activities does not allow high-tech companies to develop at lower rates; on the contrary, it enables them to expand more. Nevertheless, R&D intensity limits the growth of companies that do not have advanced technology, in spite of their R&D level.

In order to investigate the dependencies between the R&D spendings, innovation, and economic growth, Huňady & Orviská (2014) utilized the data of EU 27 member states and evaluated the nations' innovation performances via summary innovation index issued by the European Commission (2013). Besides the summary innovation index, with the purpose of detecting active changes in the countries' innovation performances, they have additionally employed the innovation growth index, which is also assessed by the European Commission (2013). It was determined that the summary innovation index value and GDP per capita rate were positively correlated countrywide. It could indicate that intensive activities of innovation can lead to accelerated economic developments and increased productivity. To put it another way, the single outcome caused by a higher GDP rate might be further innovation investments.

By using the Johansen cointegration and the vector error correction models, Bozkurt (2015) investigates the long-term connection between R&D spending and economic growth in Turkey. According to the research findings, a unidirectional causality exists from economic growth towards R&D. Long term coefficients of the R&D variable are statistically extremely significant at a positive rate. If the share of R&D in the GDP rises by 1%, the GDP's growth rate rises by 0.2630%. Gault (2015) states that attempts of countries to promote their innovation performance levels over many years results in achieving a higher economic growth rate in the future.

According to Leyden (2016), it cannot be claimed on the basis of a country's correlation assessment that the Research and Development department has a positive effect on the economy's growth level. The innovation index rate of a country and the volume of public spending on its research and development department are constructively correlated (Halsmayer & Hoover, 2016). A positive correlation can be found between the spendings in a country's R&D unit and innovation index figures such as the number of its scientific researchers (Hojnik & Ruzzier, 2016).

Janger et al. (2017) point out the constructive correlation between a country's innovation index and the GDP growth rate (Gross Domestic Product) of the economy. According to Rojas, Solis & Zhu (2018), it can be observed that if the spendings of a country's R&D unit rises, the number of researchers across the nation will automatically increase. Lerner & Stern (2019) present that increasing a country's innovation operations boosts the pace of its efficient economic growth, leading to a high productivity rate.

3. Methodology

For the analyzes, cross-sectional dependence and homogeneity tests were performed; Maddala & Wu (1999), Choi (2001), and Im, Pesaran & Shin (2003) first-generation unit root tests were applied; the stationarity was tested by CADF test from the second-generation unit root tests; Westerlund & Edgerton (2007) LM Bootstrap Panel Cointegration test was utilized to determine the long-run relationship between the variables. After long-run coefficient estimations were performed through FMOLS, Dumitrescu & Hurlin (2012) causality test was applied.

3.1. Description of the Data

In the study, BRICS_T countries were examined for the years 2007-2019, and panel cointegration analysis was applied to determine the relationship between the independent variable, R&D expenditure to GDP ratio (R&D) and the dependent variable, global innovation index (GII). The data were generated from the database of www.worldbank.org. The analyzes were obtained employing the Gauss codes and EViews 10.0. The variables used in the model are presented in Table 1.

Table 1. Description of the Variables Used in the Analysis.		
Variable	**Indication**	**Description**
R&D expenditure to GDP (ratio)	R&D	Independent variable
Global innovation index	GII	Dependent variable

3.2. Cross-sectional Dependence and Homogeneity Test

The cross-sectional dependence between the series was determined through the LM CD test developed by Pesaran (2004) and the LM adj. test, whose deviation had been corrected by Pesaran et al. (2008), and the test results are presented in Table 2. Since the probability values of the test results were less than 1% and 5%, the null hypothesis (no cross-sectional dependence) was rejected, and the cross-sectional dependence was identified between the series. Additionally, homogeneity of cointegration coefficients was tested using the delta tilde and adjusted delta tilde tests of Pesaran & Yamagata (2008), and the test results are presented in Table 2.

Table 2. Cross-sectional Dependence and Homogeneity Test Results.		
Cross-sectional dependence test (H_0: No cross-sectional dependence)		
Test	**Test statistics**	**p-value**
LM (Breusch & Pagan (1980)	12.841	0.000
LM_{adj} (Pesaran et al. (2008)	36.015	0.000
LM CD (Pesaran (2004)	14.732	0.001
Homogeneity test (H_0: Slope coefficients are homogeneous)		
Test	**Test statistics**	**p-value**
Delta_tilde	12.667	0.015
Delta_tilde_adj	15.233	0.000

Since the probability values of the test results were less than 1% and 5%, the null hypothesis (The slope coefficients are homogeneous) were rejected, and the cointegration coefficients were ascertained to be heterogeneous.

3.3. First and Second Generation Unit Root Test Results

First-generation unit root tests are divided into two as homogeneous and heterogeneous models. Since the coefficients were identified as heterogeneous, Maddala & Wu (1999), Choi (2001), and Im, Pesaran & Shin (2003) first-generation unit root tests were used.

Table 3. Panel Unit Root Test Results.

Variables	Maddala & Wu Test		Choi Test		Im, Pesaran & Shin Test	
	Level	First difference	Level	First difference	Level	First difference
	Trend + Constant	Constant	Trend + Constant	Constant	Trend + Constant	Constant
R&D	0.326	0.000*	0.265	0.006*	0.372	0.000*
GII	0.228	0.000*	0.230	0.000*	0.109	0.004*

** Stationary variable for 0.05, Probability (p) values are given in the table. The null hypothesis of the tests is as there is unit root. The optimal lag length was determined using the Schwarz information criterion.*

As can be observed in Table 3, in their level values, every variable possesses a unit root. In contrast, the first-order difference series do not comprise unit roots. Therefore, it is seen that all variables are I (1), in other words, they are stationary for the first-order difference. First-generation unit root tests are based on the assumption that the cross-sectional units forming the panel are independent and that all the cross-sectional units are equally affected by a shock occurring to one of the units forming the panel. It is a more realistic approach that a shock to a cross-sectional unit which constitutes the panel would affect other units at different levels. In order to resolve this deficiency, second-generation unit root tests that analyze stationarity considering the dependence between cross-sectional units have been developed. If the presence of cross-sectional dependence in the panel data set is rejected, the 1st generation unit root tests can be used. However, if there is cross-sectional dependence in the panel data, using 2nd generation unit root tests ensure a more consistent, efficient, and powerful estimation. In this study, second-generation unit root tests were used since cross-sectional dependence was determined. CADF, one of the second-generation unit root tests, was used. The results of the CADF test developed by Pesaran (2007) are given in Table 4.

Table 4. Second Generation Panel CADF Unit Root Test Results.

Variables	Level		First Difference	
	Constant	Constant + Trend	Constant	Constant + Trend
R&D	-1.109	-1.052	-9.462*	-9.887*
GII	-0.953	-0.915	-8.367*	-9.104*

** For 1% and 5%, H_0 is rejected, stationary variable*

In the CADF tests, the maximum lag length was used as 2, and the optimal lag length was determined according to the Schwarz information criterion. It is observed that the null hypothesis is rejected at the significance level of 1% and 5%. Unit root test results show that the series are not stationary at the level, in other words, they contain unit roots, and the variables are stationary at the I(1) level.

3.4. Panel Cointegration Test

In this study, the LM bootstrap panel cointegration test developed by Westerlund and Edgerton (2007) to determine the long-term relationship between variables was employed. In this cointegration test, the dependence between the cross-sectional units is taken into consideration, and it has been observed that the test gives sound results in small samples. In this test, the H0 hypothesis cannot be rejected, indicating that there is a cointegration relationship for all cross-sections.

Table 5. Westerlund & Edgerton (2007) LM Boostrap cointegration test results.

	Constant			Constant + Trend		
LM_N^+	**Statistic**	**Asymptotic p-value**	**Bootstrap p-value**	**Statistic**	**Asymptotic p-value**	**Bootstrap p-value**
	9.664	0.271	0.369	9.327	0.294	0.369

Bootstrap probability values were obtained from a distribution of 10,000 iterations. Asymptotic probability values were acquired from the standard normal distribution. It is seen that there is a cointegration relationship between the series for the country group ($p > 0.05$). In this case, the series move together in the long run. Once it is confirmed that the series are cointegrated, the coefficients in the model can be estimated through the cointegration estimators. Long-run coefficients of the model were estimated through FMOLS by taking the first-order differences of the variables.

3.5. Long-Run Cointegration Coefficients Estimation via FMOLS (Fully Modified OLS)

In this study, long-run cointegration coefficients were examined by FMOLS (Fully Modified OLS) method. The FMOLS method eliminates second-order bias effects, as it takes into account the simultaneous relationships between error terms of equations of the variables. The FMOLS estimator resolves diagnostic problems that occur with standard estimators. This method was developed by improving OLS, taking into account the autocorrelation problem.

Table 6. FMOLS Long-Run Cointegration Coefficients.

Countries	D (R&D)
Brazil	0.042*
Russia	0.061*
India	0.055*
China	0.069*
South Africa	0.036*
Turkey	0.030*
PANEL	0.043*

** Statistically significant variable for 0.05, D represents the first-order difference.*

A statistically significant positive impact of R&D on global innovation index GII was determined for the countries addressed. The highest effect level was obtained for China and Russia.

3.6. Causality Analysis

The causality test to be employed varies according to whether a cointegration relation exists between the panel series. All panel causality tests perform estimates under the assumption of horizontal cross-sectional independence. Through the Dumitrescu & Hurlin (2012) test, both horizontal cross-sectional dependence and cross-sectional independence can be estimated, and effective results can be reached. The Dumitrescu & Hurlin (2012) test shows similarity to the Granger causality test for heterogeneous panels. This test signifies the average of individual Wald tests calculated for horizontal cross-section units within the Granger causality test. This test takes into consideration both heterogeneity and cross-sectional dependence. Another feature of the Dumitrescu & Hurlin test is that it works both in the presence and absence of a cointegrated relationship. In the panel causality test, three different statistical values are calculated.

Table 7. Dumitrescu & Hurlin (2012) Test Results.

Null hypothesis	Test	Statistical values	p
The variable R&D is not the Granger cause of the variable GII	*Whnc*	5.731	0.013
	Zhnc	6.893	0.006
	Ztild	6.112	0.000
The variable GII is not the Granger cause of the variable R&D	*Whnc*	6.324	0.002
	Zhnc	7.542	0.000
	Ztild	7.093	0.014

As can be seen from Table 7, the two-way causality was detected between the R&D and GII variables. The variable R&D is the Granger cause of the variable GII, at the same time the variable GII is the Granger cause of the variable R&D (R&D ↔ GII).

4. Conclusion

In the study, BRICS_T countries were examined for the years 2007-2019, and panel cointegration and causality analyses were applied to determine the effect of the R&D expenditure-to-GDP ratio (R&D) on the global innovation index (GII). Based on the study, a statistically significant positive effect of R&D on global innovation index GII was determined for the countries. The highest impact rate was obtained for China and Russia. For the overall panel, an enhancing effect of 4.3% was determined. As a result of causality analysis, a two-way causality was detected between the R&D and GII variables. Although it expresses a concept beyond Research and Development (R&D) activities, the concept of innovation, which is often perceived as an output of R&D activities, has a positive impact on sustainable growth and development within the context of its role in increasing employment, boosting productivity and enhancing competitiveness. However, in Turkey, the fact that the effect of R&D expenditures to GDP ratio on the global innovation index has been realized at the lowest level among BRICS_T countries shows that the benefits expected from innovation itself cannot be achieved continuously and effectively. In this context, it is thought that an ecosystem in which the control mechanism, an element of R&D and innovation-oriented legislation, is operated more effectively will be beneficial. Besides, when determining the right position for itself in the global economy, it is also important to design and implement the right economy, finance, industry, and trade policies regarding the products and services to be offered to the market. Having an ecosystem suitable for the production of goods and services attracting the market will be able to make the national economy stronger, due to the increase in the qualified labor force, employment, export level, national income level, and competitive power.

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CHAPTER 5

STATISTICAL MACHINE LEARNING IN TERMS OF INDUSTRY 4.0 AND INVESTIGATION OF THE IMPACT OF BIG DATA ON THE COMPETITIVENESS OF FIRMS

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Abstract

The ultimate goal of Industry 4.0 is to deliver real-time data to network-based information technology systems, which are always connected to machines, components, and ongoing work. They use machine learning and artificial intelligence algorithms to analyze and obtain information from these big data and adjust processes automatically as needed. Statistical machine learning techniques are designed to extract information from existing data. Statistical machine learning is largely based on statistical optimization and forecasting techniques. As a result of the analysis of big data gathered by statistical techniques with statistical machine learning methods, both manufacturers and service sector companies using these new techniques and methods have higher competitive power compared to companies that cannot adapt to these new techniques. In this study, statistical machine learning in terms of Industry 4.0 and the effect of big data on the competitiveness of firms have been investigated.

Keywords: Industry 4.0, Statistical machine learning, Big Data, Competition, Innovation, Innovative solutions.

1. Introduction

The initial Industrial Revolution, which covered the second half of the 18th century and the first half of the 19th century, changed the world into a system where manual methods were replaced by mechanical, motorized production processes and vehicles. After all, the first Industrial Revolution resulted in the mass production and factory system.

After rapidly-passing 200 years, today, the fourth industrial revolution of the industry conquers 21st-century manufacturers - Industry 4.0. The latest digital technologies are used for optimizing and mechanizing the manufacturing, including high-level supply chain processes. The final purpose of Industry 4.0 is to provide real-time data to network-based IT systems by always-connected sensors implanted in machines, parts, and continuous work. They use machine learning and artificial intelligence algorithms to analyze and obtain information from these big data and to automatically adapt processes as required.

The challenges of contemporary production systems are growing complexity, dynamic features, high-dimensionality, and disordered structures. Fast-paced advances in the field of algorithms and increasing the usability of data (for example, due to low-cost sensors and switching to intelligent production) and with the increasing computing power, especially applications for machine learning in manufacturing are increasing rapidly. Today, controlled algorithms provide superiority in most applications in the field of production. However, supervision and learning techniques are rapidly gaining in importance due to the rapid increase in existing data, more and better sensor technologies, and increase in awareness. Even in today's technology, hybrid approaches are actively used. This has made it a necessity to consider Big Data developments in recent years and to use them widely in all areas. Intelligent production systems for many applications in the production area and intelligent machine learning techniques, and big data are powerful tools, and their importance will further increase in the future. With their interdisciplinary nature, machine learning and big data techniques provide great opportunities for new developments in competitive power. However, this interdisciplinary character also maintains its importance as an important risk factor, which is essential for the development of cooperation among different disciplines such as Computer Science, Industrial Engineering, Mathematics, Statistics, and Electrical Engineering simultaneously against today's firms.

Today, the manufacturing industry is experiencing a data increase that has never been seen before. These data are collected raw from semantics, quality, from various forms such as sensor data, environmental data, machine tool parameters from the production line.

Different names can be used for this phenomenon, for example, Industrie 4.0 (Germany), Intelligent Manufacturing (USA), and Intelligent Factory (South Korea). These large amounts of data increase and availability are often referred to as Big Data. In general, the manufacturing industry can be concluded safely, to benefit from extended data accessibility, for example, quality improvement actions, production cost estimation and/or process optimization, a better comprehension of customer needs, etc., for this, it also requires support to address relevant high-dimensionality, complexity, and dynamics.

New developments in some areas, such as mathematics and computer science (e.g. statistical learning) and the existence of easy-to-use, usually freely available (software) tools, offer a great capacity to ensure a sustained grasp of the production area and their growing production data warehouse. One of the most exciting developments is in the field of machine learning (data mining, artificial intelligence, data discovery from databases, etc.). Nonetheless, the area of machine learning is highly diversified and there are a lot of different algorithms, theories, and methods utilizable. For numerous manufacturing practitioners, this constitutes an obstacle to the adoption of these powerful tools and can, therefore, prevent the use of an increasing amount of available data.

In many mature economies, the contribution of production to GDP has declined over the last decade, becoming a major problem. It is also known that a number of important initiatives have been started to renew the manufacturing sector in recent years. President Obama's announcement of new action plans in 2014 under the title "Enforcement Actions to Strengthen Advanced Manufacturing in America" to further strengthen US manufacturing is an example of these initiatives. Again, the European Union's "Factories of the Future" initiative in 2016 is another example of these initiatives. The challenges facing production now are very different from those experienced before.

There are many pieces of research suggesting the key challenges of production at the global level. It is possible to summarize the key challenges that most researchers address as follows:

- Adoption of sophisticated manufacturing technologies.
- The increasing significance of manufacturing products with high added value.
- Utilizing superior knowledge, knowledge management, and Artificial Intelligence systems.
- Sustainable production (methods) and products.
- Swift and adaptable business capabilities and supply chains.

- Innovation in products, services, and processes.
- Close cooperation between industry and research for adopting new technologies.
- Modern production management standards.

These key challenges emphasize the tendency of the production area to be more complicated and dynamic. This obvious complexity increases not only in the production programs itself but also in the processes of companies and collaborative networks (business) as well as the product to be produced. Adding the difficulty of managing and controlling complexity in manufacturing further increases the uncertainty of the dynamic business environment of existing manufacturing firms.

Artificial Intelligence and machine learning techniques make it compulsory to use techniques to manage complexity, production changes and uncertainties. In particular, in the areas that are most likely to be optimized, for example, monitoring and control, programming and diagnostics, it is seen clearly that increasing the availability of data adds another difficulty: Big amount of available data as well (e.g., sensor data), high dimensionality and diversity (e.g., different sensors due to or related processes) data, besides, production optimization problem of the complementary nature of controls. Determination of product and processing state drive in production systems using machine learning is that the subject new developments are happening. The current candidate methods to overcome some of the challenges of today's complex production systems are machine learning techniques. These data-driven methods can find rather complicated and nonlinear models in data of different types and sources, and then work on raw data by estimation, detection, classification, regression, or estimation.

2. Big Data

Most companies store and use large amounts of information. With the technical advancement that can be seen, particularly in the area of information technology, there has been a significant rise in the demands and emphasis on information storage, analysis, and processing. IBM states that we generate 2.5 million (2.5 x 1018) bytes of data daily, accordingly over the past two years, 90 percent of the data of the world has been produced. These are in the forms of electronic correspondences, broadcasts on social media, digital images, videos, invoices, sensors, and such, all of which describe the notion of Big Data (IBM, 2013).

It will be best to represent and describe the characteristics of Big Data in this chapter before defining the term of Big Data. It is nearly improbable to attain a precise and uniform definition of Big Data, as this notion is not formally codified or integrated. Here, various acknowledged definitions of Big Data will be presented for a better apprehension of the notion.

A conventional and very common definition was composed by the McKinsey Global Institute: (McKinsey Global Institute, 2011): “Big Data indicates information sets which surpass in size the capacity of standard database program tools to acquire, store, handle, and evaluate.” The above description points out a Big Data-related concern that businesses encounter. The volume and variety of information are so vast and diverse that companies can not operate using conventional systems and instruments that they are used to.

In his article titled “Big Data”, John Gantz explained as follows (Reinsel - Gantz, 2011): “Big Data technologies represent the systems and structures, which are created for efficient data generation from a broad spectrum of information, high-velocity capture, detection, and/or analysis.” The mentioned definition is designated as a worldwide term for immense and complicated technology clusters intending for controlling and analyzing Big Data, which is unorganized information essential to an enterprises' management and growth. One aspect of the whole concept was defined by Douglas Beyer as follows (Laney - Beyer, 2012): "Big data are high-volume, high-speed, and/or high-variety information assets that require new processing forms for advanced decision making, insight exploration, and optimization of the processes”. With this in mind, Big Data signifies sets of data that are not able to be saved or processed employing standard techniques and instruments; this indicates that it is challenging to process them since they cannot be stored in one place, but they must be distributed.

2.1. Key features of Big Data

Even though definitions of Big Data are not coherent, they all refer to three main points (Big Data of 3) that distinguish them from normal data. The first is the volume of data, then the frequency of generating new data, and finally the speed, which is diversity as the form of the data. More features can be added since the Big Data recognition process has just started.

The main characteristic of Big Data is the volume, to put it another way, the data quantity. It is possible to describe it as the physical potential at which it can be utilized (in fundamental classifications, this capacity is gauged between terabytes and petabytes), or measurements can be conducted via the values of the records, transactions, tables or files.

As businesses concentrate on the fact that data is an asset, their reluctance to dispose of data and reduce their size increases. This matter, at the same time, concerns the loss of the relative value of each additional byte. The reverse situation concerns the increase of the relative value of every extra data storage unit needed for data protection.

Velocity can be defined as the production speed of Big Data. At the same time, it can be understood as the time period from transferring data to making the decision by one's own, from the moment the data is received to the moment it is analyzed.

Speed can still be considered a feature that increases its significance, yet it can be presumed that it will have the highest importance compared to other features. This assumption is verified by the reality that many sectors require real-time data processing, and that their judgments almost entirely depend on those data.

Data diversity is the principal constituent of Big Data. Traditional information which is organized is usually called as structured data. A good exemplar of this information is the data stored in the storage structures in databases. In recent years, however, it has been mostly classified as unstructured content and semi-structured content.

There can be numerous types of unstructured content and describing them in depth is not easy. A vast majority of the contemporary formats are included in this group, comprising audio and video data, social network records, blogs, information of geolocation, network click logs, the information accessible on the Internet, and more.

Big Data is aimed at adopting and incorporating all the abovementioned information, integrating those in the form appropriate for subsequent company procedures.

2.2. Using Big Data for the Company's Competitive Edge

Then, why is Big Data or the technology of Big Data so essential to businesses? Above all, they make it easier to comprehend and infer meaning from all information fields in the world. Corporations and organizations have collected and stored data which are parts of each transaction. All that information has been essentially utilized to monitor or predict the future. Nowadays, these data are bursting. It is probable to collect information on every subject.

For instance, customers visiting a company's website, thus, marketing professionals can accumulate information about each consumer who is interested in their brand or product.

All those resources are like a treasure for businesses because they can give the companies a point of view of the consumers' mind. Nonetheless, this necessitates the implementation of new methods, technologies, and mechanisms termed Big Data. The information is here and withholds precious data, you merely need to find a system to investigate how to do it.

It will be appropriate to mention a very real comparison that has been discussed in recent years. Besides, this is where garbage is collected, as well as data, given the issues of polluting the Earth. It's up to us if we leave the trash on the ground, pick it up and allow it to pollute the planet later, or we take and recycle it. The same problem applies for Big Data, the data in corporations is the same as waste and the same lies, no one uses them, and they just "pollute" the computer. We must use these data for our own benefit. Wherever we look, we are surrounded. If this “garbage” is put into the required form, we can make use of it and raise its value in the future.

Big Data solutions are not only perfect for examining raw structured data but also for examining semi-structured and unstructured data from any sources mentioned in the prior section. Additionally, Big Data solutions are excellent if the entirety or the majority of data requires to be examined, or if exemplification from the data is not as effective as a larger data set.

As reported by McKinsey Global Institute, Big Data is able to create value in five ways (McKinsey Global Institute, 2011):

- It can form a transparent environment by making the new potential more widely available.
- Allows companies to conduct experiments. For example, they can conduct experiments on process changes and examine big quantities of information obtained from these studies in order to recognize the potential efficiency enhancements.
- Big Data is utilizable to produce a more comprehensive client segmentation to individualize the information processing as well as arrange customer-specific services.
- Examination of Big Data might assist humans in making decisions by indicating the latent connections or some concealed perils. For instance, insurance firms might have machines that perform risk or fraud assessments. Decisions of lower complexity might be mechanized utilizing these systems.
- Data may further enable the introduction of innovative business models, goods and services, or upgrade those available. It is possible to employ data on how goods and services are used to originate and refine modern models of products.

Companies can achieve a high competitive edge and outperform their competitors by employing Big Data and making use of its advantages. While Big Data is less understood, it offers businesses greater growth potential than traditional technologies. Corporations which are more improved in this sense and appreciate the value of Big Data more quickly, can succeed to get a leadership status in their industries in terms of competition. The significance of this notion should not be overlooked by businesses.

2.3. Industry 4.0 and Big Data

As we said before, manufacturers have been producing plenty of data in terms of real-time production and quality for a while. Nonetheless, there are not sufficient platforms, which can hold various sources of data regarded trash and deduce comprehensive insights to enhance quality, productivity, and such, therefore, it is quite common that these isolated data lakes are "wasted". To put it another way, the problematic issue is about the capability of efficiently deriving value from data, not about producing and accumulating it.

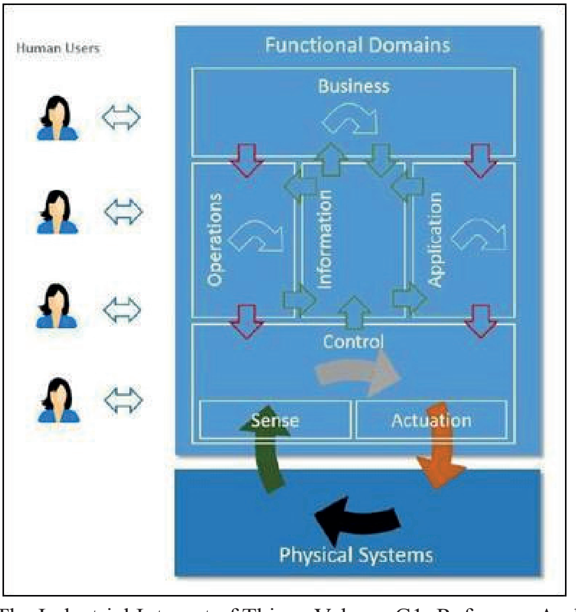

Figure 1: Sources: The Industrial Internet of Things Volume G1: Reference Architecture, Industrial Internet Consortium

Industry 4.0 big data comes from many and various sources:

- Threshold characteristics such as product and/or machine design data
- Machine processing data obtained from control systems
- Data of product and process quality
- Manual transaction records performed by personnel
- Manufacturing Execution Systems
- Information on production and operating costs
- Fault detection and other installations for system monitoring
- Logistics-related information, including third-party logistics
- Customer data regarding product usage, feedback, and more

Some of those data sources are structured as we have previously explained (such as sensor signals), some are semi-structured (such as manual transaction records), and some are not fully configured (such as image files). However, in most circumstances, most of the data is not used or is used only for very certain tactical objects. A key factor in, generally not strategically, exploiting Industry 4.0 big data is poor interoperability between incompatible technologies, systems, and data types; a second key factor is that traditional IT systems do not store, manipulate and manage those large data volumes at high speeds.

What businesses need, therefore, are state-of-the-art programs which can completely enhance big data generation utilizing machine learning, artificial intelligence, and predictive analytics.

Today, by gathering, evaluating and exchanging information in all main functional areas, production companies are attempting to obtain real business intelligence. Not only are manufacturing technologies more effective in this architecture, but they can also react in time to altering company requirements, including messages from associates and clients.

The model below focuses more on large data and analytical flows at plant and factory levels.

Low (orange) stacks collect, process, and analyze data flow from the production area quickly and scalably. The upper (blue) stacks are likely for large-scale and intense batch analyses applied in cloud-based Big Data frames. It can be seen that the bulk analytical stack, at the same time, receives stored plant/factory big data as an input. In order to optimize production processes and applications, both flow and batch analysis outputs are distributed as information.

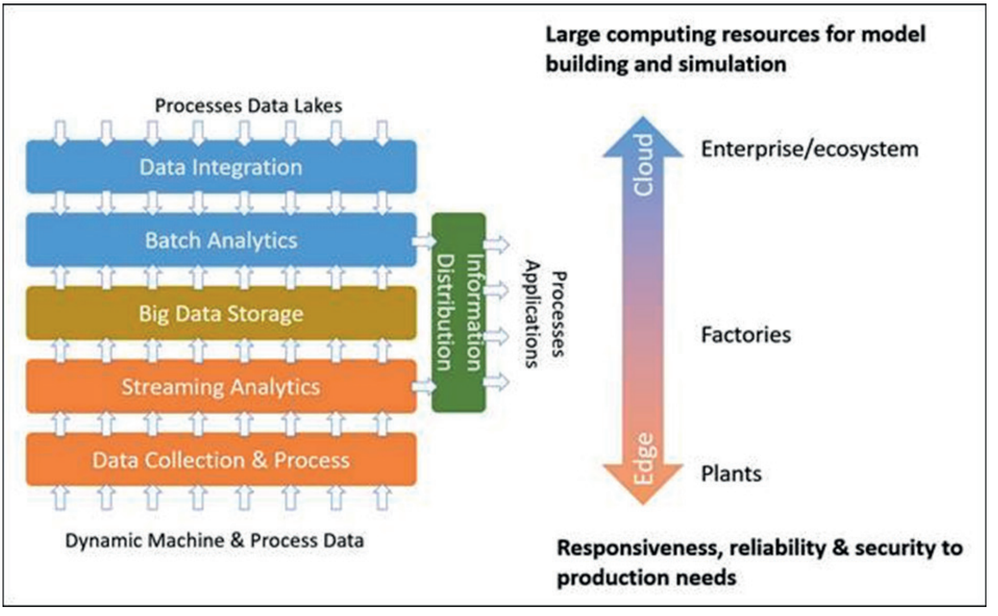

Figure 2: Source: Shi- Wah Lin, IIoT (The Industrial Internet of Things) for Smart Manufacturing part 3 - A New Digitalization Architecture, October 16, 2017

2.4. Industry 4.0 Big Data Usage Examples

In 2016, PwC carried out a worldwide survey of the adoption of Industry 4.0 in a wide range of industries, including automotive, electronics, industrial manufacturing, aerospace, and defense and security. Surveyors expected that 2020 Industry 4.0 applications, including big data analytics, would decrease production and operating costs by 3.6%, resulting in cumulative savings of $ 421 billion.

The following are several chosen real-life instances showing how the Industry 4.0 big data vision can add assessable value to manufacturing businesses:

Combining data of quality and production for improving the quality of production: A semiconductor producer started to associate the single-chip data seized at the end of the production process with the process data previously obtained from the process. The producer can thus detect faulty chips early, and remarkably enhance the quality of the manufacturing process.

Empowered clients: The automotive industry embraces Industry 4.0 with enthusiasm to fulfill customer expectations in a cost-effective way for further economic and digitally connected automobiles. Most use cases of large data to be produced by the connected means include continuous data exchange with the manufacturing company. In addition to improving the after-sales service to the individual vehicle owner, aggregate data on vehicle performance can be employed to enhance quality processes and future designs.

Reduced downtime: Industry 4.0 large data analytics, applicable to many industrial sectors, can reveal guides predicting mechanical or procedural failures before they happen. Machine supervisors can evaluate the processes or machine performances in real-time, and in most circumstances avoid unplanned downtime.

Industry 4.0 recommends predictive production in future industries. The machines are connected as a common community. This evolution requires the use of prediction tools, thus data can be systematically translated into information which is able to clarify uncertainties, and in this way makes more "informed" decisions possible.

This includes industrial big data, that makes manufacturing services and production analytics more important than in previous years, which changed the value proposition of manufacturers. In order to continue with these trends, a systematic framework is proposed for self-recognizing and self-servicing machines. The framework includes the concepts of cyber-physical system and decision support system.

To summarize, the prognostic monitoring system is a trend of intelligent production and industrial big data environment. There are many areas where four key domains are envisaged to be effective in the emergence of the fourth industrial revolution:

- Machine health forecasting will reduce machine downtime and support the ERP system to optimize prognostic information, production management, maintenance timing, and guarantee machine safety.
- The flow of information between production line, enterprise management level and supply chain management makes industry management more transparent and orderly.
- The new industry trend will reduce labor costs and provide a better working environment.
- Finally, energy savings, optimized maintenance schedule, and supply chain management reduce costs.

3. Statistical Machine Learning

In this part of the study, first of all, the primary benefits, difficulties, and requirements of machine learning applications related to production will be explained. Next, the current state of the art in the field of machine learning will be reviewed by focusing again on manufacturing applications. In this context, different machine learning techniques and algorithms configuration will be developed and presented.

Advantages of the machine learning application over today's production challenges:

Machine learning is often known for its capability to deal with many problems of nature that arise in the field of intelligent production.

It offers soft computing and hybrid artificial intelligence approaches to intelligent production.

The implementation of machine learning techniques has, in the last 20 years, been due to several factors, for example; Increased presence and strength of existing Machine learning tools and the existence of big amounts of complicated data with a small degree of transparency.

The main definition of Machine learning, however, allows computers to solve problems before they are specifically programmed.

At present, machine learning is already in different production areas, for example; optimization, control, and troubleshooting.

Many machine learning techniques (e.g. Support Vector Machine [SVM]) are designed to analyze large amounts of data and handle high dimensionality (> 1000) very well.

However, accompanying considerations, such as possible over-fitting, should be considered. It supports vector machine for machine status monitoring and diagnostics.

If dimensionality arises as a problem despite the possibility of the power of algorithms, there are possible techniques to decrease the dimensions. These decrease the effect of diminishing dimensionality on expected results.

The importance of using machine learning is that in this circumstance, SVM dimensionality is not a practical problem, and thus, the need to reduce dimensionality is decreased. This indicates the possibility of being more flexible in containing apparently unrelated information in manufacturing data, which might be related in particular situations. This might have an immediate effect on the present information gap previously defined.

The application of machine learning in production can lead to the acquisition of patterns from existing datasets, which may form the basis for developing approaches for the future behavior of the system.

This recent information can assist process owners when making decisions, or can be utilized automatically to enhance the system immediately. Finally, the purpose of some machine learning techniques is to identify specific patterns or orders that define relationships.

Considering that machine learning, which is a rapidly changing, dynamic production environment, is a component of artificial intelligence, and the difficulty of inheriting the ability to learn and adapt to changes, the system designer does not need to provide solutions for all possible situations.

Therefore, it provides strong arguments that applying machine learning in production may be beneficial, given the challenge of most first principle models in dealing with adaptability. Learning and adapting automatically from changing environments is a major strength of machine learning.

Machine learning techniques are designed to extract information from existing data.

Alpaydin (2010) emphasizes that stored data will only be useful when analyzed and, for example, converted into information that we can use to make predictions.

This is especially true for production when struggling to obtain real-time data throughout a live production program that has technical, financial, and information-related limitations. This can also be effective in positioning process control points (Wuest, Liu, Lu & Thoben, 2014).

Although it is logical to carefully select control points regardless of which data are useful, given the analytical power of machine learning techniques, it may not be possible to obtain information from previously futile data. This may end up with the capacity to collect further data in the whole production schedule. It is a clear question of whether this is useful or not. Considering the ability of machine learning to manage high-dimensional data, the technical side of examining extra data is not difficult. Nevertheless, with regard to data capture, especially the ability to collect data can still be a problem. When data are obtained, the identification of status drives is not considered problematic and is not repeated frequently in very high dimensional situations.

The table below provides a review of the theoretical capabilities of machine learning methods to address the principal challenges in manufacturing applications (requirements) (Table 1).

Table 1: Source: Thorsten Wuest, Daniel Weimar, Christopher Irgens & Klaus- Dieter Thoben Machine learning in manufacturing: Advantages, challenges, and applications, Journal of Production & Manufacturing Research, Volume 4, 2016 - Issue 1

Table 1. Summary of suitability of ML techniques in manufacturing application.

Manufacturing requirement	Theoretical ability of ML to meet requirements
Ability to handle high-dimensional problems and data-sets with reasonable effort	Certain ML techniques (e.g. SVM) are capable of handling high dimensionality (>1000) very well. However, accompanying issues like possible over-fitting has to be considered (Widodo & Yang, 2007; Yang & Trewn, 2004)
Ability to reduce possibly complex nature of results and present transparent and concrete advice for practitioners (e.g. monitor XX and parameter YY at checkpoint ZZ)	ML may be able to derive pattern from existing data and derive approximations about future behavior (Alpaydin, 2010). This new information (knowledge) may support process owners in their decision-making or used to automatically improve a system
Ability to adapt to changing environment with reasonable effort and cost. Ideally a degree auf 'automated' adaptation to changing condition	As ML is part of AI, and thus be able to learn and adapt to changes, 'the system designer need not foresee and provide solutions for all possible situations' (Alpaydin, 2010). Learning from and adapting to changing environments automatically is a major strength of ML (Lu, 1990; Simon, 1983)
Ability to further the existing knowledge by learning from results	ML can contribute to create new information and possibly knowledge by, e.g. identifying patters in existing data (Alpaydin, 2010; Pham & Afify, 2005)
Ability to work with the available manufacturing data without special requirements toward capturing of very specific information at the start	ML techniques are designed to derive knowledge out of existing data (Alpaydin, 2010; Kwak & Kim, 2012). 'The stored data becomes useful only when it is analyzed and turned into information that we can make use of, for example, to make predictions' (Alpaydin, 2010)
Ability to identify relevant process intra- and inter-relations & ideally correlation and/or causality	The goal of certain ML techniques is to detect certain patterns or regularities that describe relations (Alpaydin, 2010)

3.1. Structuring machine learning techniques and algorithms

In recent years, machine learning has been used within a wide range of research and applications. This has led to various subfields, algorithms, theories, application fields and such. Different researchers choose different approaches to construct the area. The following figures illustrate these algorithms (Figure 1, 2, 3).

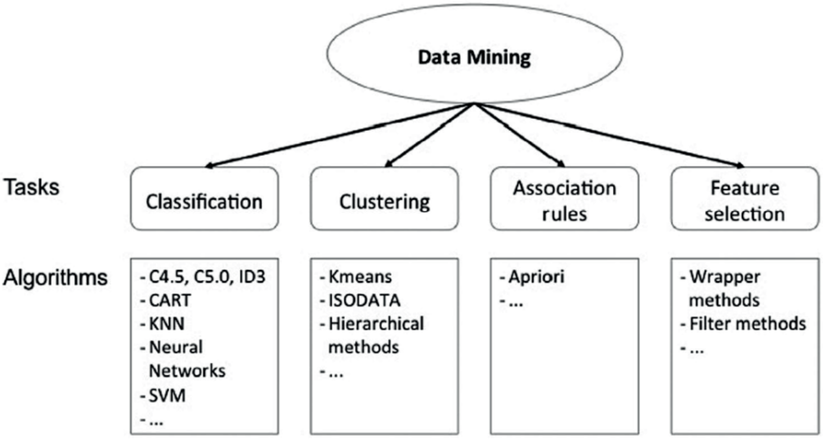

Figure 3: An overview of tasks and main algorithms in DM (Corne et al., 2012)

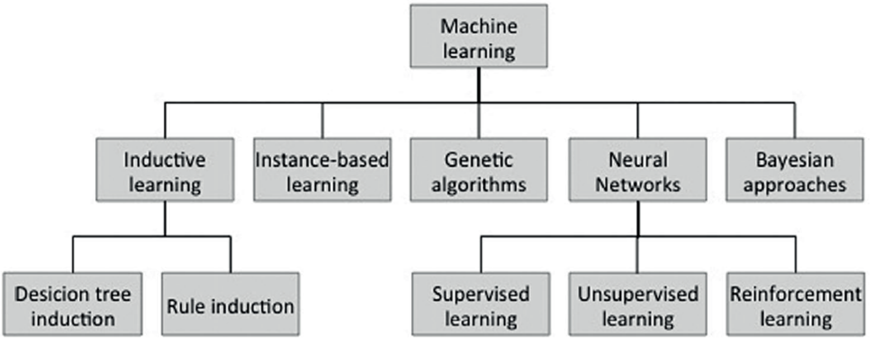

Figure 4: Classifications of main ML techniques according to Pham and Afify (2005)

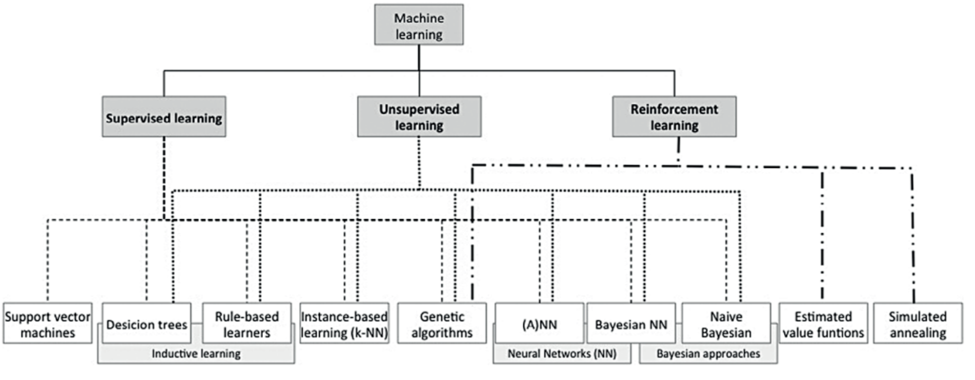

Figure 5: Structuring of ML techniques and algorithms

As a result, machine learning is largely based on statistical optimization and forecasting techniques.

Basically, these techniques can be grouped under three headings:

1. Uncontrolled machine learning: The definition is that there is not any feedback given by an external teacher/knowledgeable specialist within uncontrolled learning. It has introduced the rule that the algorithm itself, eg. if examples of conceptual integrity of the attributes are not tagged (no known labels and no correct corresponding outputs), is probably uncontrolled learning. The aim is to explore categories of objects which are unknown by clustering. Particularly in the context of Big Data, uncontrolled techniques are becoming more and more important. Nevertheless, as with the production practice, the basic hypothesis is that knowledgeable specialists can give feedback on the sorting of states to define the learning set to train the algorithm.

2. Reinforcement learning: Reinforcement learning is described by the supply of educational information by the environment. A digital boost signal provides data about the performance of the system in a particular sequence. Another descriptive characteristic is that the student should try to find out the actions giving the optimal outputs (digital amplification signal) by testing instead of being told. This distinguishes reinforcement learning from most other methods of machine learning. However, reinforcement learning is regarded by some researchers as "a special form of supervised learning".

3. Supervised machine learning: In manufacturing practice, usually, supervised machine learning methods are implemented because the problems are intense in data, yet less in knowledge. In addition, supervised machine learning can benefit from data collection in manufacturing for statistical process control purposes, and based on that this data is mostly tagged, supervised machine learning is in the manner of learning from examples provided by a knowledgeable external auditor. Once an algorithm is selected, it is trained to utilize the training data set. To assess the capability to fulfill the intended task, the trained algorithm is assessed via a set of evaluation data. Dependent on the achievement of the algorithm trained by the evaluation algorithm, parameters can be set to optimize achievement if the achievement is already good. If the performance is unsatisfactory, the procedure should be restarted in a prior stage, based on the actual performance.

In principle, 70% of the data set is employed as a training data set, 20% as an assessment data set (for setting parameters – e.g. bias) and 10% as test data.

4. Conclusion

The ultimate goal of Industry 4.0 is to deliver real-time data to network-based information technology systems, which are always connected to machines, components, and ongoing work. They use machine learning and artificial intelligence algorithms to analyze and obtain information from these Big Data, and adjust processes automatically as needed. Statistical machine learning techniques are designed to extract information from existing data. Statistical machine learning is largely based on statistical optimization and forecasting techniques. As a result of the analysis of Big Data gathered by statistical techniques with statistical machine learning methods, both manufacturers and service sector companies using these new techniques and methods have higher competitive power compared to companies that cannot adapt to these new techniques.

Big Data brings several advantages to companies. It makes the information inside more transparent. It provides a wider, deeper and more accurate insight. Therefore, it also improves decision-making. It allows companies to create a more complex and complete image of their customers and therefore, offers more accurately designed products and services.

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CHAPTER 6

THE ROLE OF OPEN MARKET AND EDUCATION ON INNOVATION IN EMERGING ECONOMIES

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Abstract

The processes of globalization and liberalization have raised the competitiveness considerably in the world and made the innovation mandatory for firms and nations to survive. In this study, we explored the effects of trade liberalization together with FDI inflows and education on innovation on a sample of emerging economies over the period 1995-2017, by using panel cointegration and causality analyses. The findings revealed that trade liberalization, FDI inflows and education have a significant positive impact on innovation.

Keywords: Innovation, Trade liberalization, Foreign direct investment inflows, Education, Panel cointegration and causality analyses.

1. Introduction

Despite all the efforts made during time to reduce the economic gaps between countries, the nowadays reality presents a world in which these gaps are getting wider and wider. In order to stop this phenomenon, the developing and especially the less developed economies should focus their attention on the most valuable asset of a nation: the human capital. Only by doing this, they will be able to get closer to the developed states' level because, as Heyne, Boettke and Prychitko (2013) stated, the less developed states do not lack things, but ideas. Innovation, which represents the process of introducing new ideas into an economy (Lundvall, 2008), may transform the existing markets, or even create new ones, and stimulate the economic growth (Marvel and Lumpkin, 2007). The explanation is related to the fact that innovation, which occurs in the process of collective entrepreneurship (Christensen and Lundvall, 2004), enhances the business development and, therefore, the long-term wealth creation (Ahuja & Lampert, 2001).

In this context, two main questions are raised: Where can the less developed states take the money from, in order to be able to invest in education and, implicitly, in innovation? What skills could make a person more efficient in this era of rapid changes?

At the first question, many economists pointed to the international trade and foreign investors. Faced with increasing international competition, innovation has been placed in the core of firms' long-term strategies. If, initially, the economic literature paid attention especially to the role of internal research and development (R&D) on firms' innovation capability (Dosi, 1984), lately, researchers argued that the ability to exploit external knowledge is vital for the innovation process of a company (Teece, Pisano and Shuen, 1997). In the context in which innovation results more and more from the interaction of a large number of companies, an important aspect in the innovation management is the optimal integration of external knowledge (Veugelers and Cassiman, 1999).

There are several important channels through which attracted foreign direct investment (FDI) can stimulate the innovation in the host country (Blomstrom and Kokko, 1999). First of all, it is generally agreed that domestic companies can learn about the new products and technologies brought in by foreign investors (Cheung and Lin, 2004). Secondly, apart from the technological spillovers, the local firms can get the know-how of foreign companies by stealing their skilled workers (Aitken and Harrison, 1999). The third channel refers to the FDI's effect on local R&D activity. The presence of the foreign products and technologies in the host markets can enhance local innovators to come up with new goods and processes

(Baldwin, Braconier and Forslid, 1998). Moreover, since the spillovers may also occur from foreign companies to the host country's suppliers through the technological know-how transfer, the local suppliers may also be stimulated to innovate (Smarzynska, 2002).

Trying to offer an answer to the second question, the researchers suggested that, since innovation is a process involving close interaction between individuals and organizations, the knowledge and skills obtained through formal education should be combined with social abilities (Lundvall, 2008), usually acquired through informal and non-formal education. In this context, the concept of learning economy has emerged. As Lundvall and Johnson (1994) suggest, it refers to the fact that knowledge becomes obsolete more rapidly than before and, consequently, it is necessary that firms engage in organizational learning and workers constantly attain new competencies.

Considering all these aspects, the present study intends to analyze the relationship that exists between trade liberalization, FDI and education, on one hand, and the innovation, on the other hand in 20 emerging economies, during the period 1995-2017. In order to achieve this purpose, we have used the panel cointegration and causality analyses. The paper is structured as following: the next section summarizes the literature regarding the effects of trade liberalization, FDI inflows and education on innovation, the third section presents the methodological approach and the last two parts reflect the obtained results and, respectively, the conclusions.

2. Literature Review

The literature developed the idea according to which a higher level of human capital allows a better recognition of the opportunities (Davidsson & Honig, 2003; Shane, 2000; Shepherd & DeTienne, 2005) and improved outcomes (Becker, 1964). Therefore, individuals with superior human capital will identify a larger variety of opportunities than others and, consequently, will have higher chances to choose the best option.

As stated by the human capital theory, education and experience are in the core of the concept of human capital (Becker, 1964). The experience can take many forms. While some researchers talked about the labor market experience, the management experience and the previous entrepreneurial experience (Bates, 1990; Gimeno, Folta, Cooper and Woo, 1997; Robinson and Sexton, 1994), others mentioned the business experience, the functional experience and the industry experience (Shane, 2003). Regardless of its type, the experience allows the development of certain skills, useful for the discovery and exploitation of the opportunities. However, it was noticed that greater experience might limit the strategic flexibility (Hitt & Barr, 1989), with a negative impact on innovation. A similar conclusion was drawn by Bhide (2000), who argued that very high levels of human capital might diminish the risk-taking propensity of entrepreneurs regarding the innovative new ventures.

Together with experience, education is another qualitative side of the human capital, with a vital importance in identifying and valuing the opportunities.

The formal education has a significant impact on the individuals' open-mindedness and receptivity to innovation (Kimberly and Evanisko, 1981). Considering that greater experience leads to higher business success (Singer, 1995), the association of high experience and education would definitely be a decisive factor for entrepreneurial innovation (Marvel and Lumpkin, 2007). Yet, not all types of education lead to innovation. For example, the knowledge described by Shane (2000), which involved specific skills for serving the markets and solving the customers' problems, does not seem to influence the innovation. In the meantime, the technology knowledge proved to be a prerequisite for recognizing the opportunities and enhance the innovation (Marvel and Lumpkin, 2007). Moreover, combining the technology knowledge with the market knowledge will lead to new ideas (Amabile, 1998), because, as Amabile (1998) noticed, an individual's creativity is enhanced if more knowledge types are used. O'Conner and Veryzer (2001), analyzing the impact of using different types of knowledge on innovation, reached similar results.

Varsakelis (2006) focused the attention on the formal education and showed that those states that are investing more in the quality of mathematics and science at all three levels are more likely to have higher innovative results.

One of the main questions raised by the researchers referred to the extent to which the educational system is able to produce the knowledge, skills and abilities required by an innovative business environment (Toner, 2011). Most of the analysts agreed that, for coping with the requirements of an innovative market, the formal education should enhance the development not only of literacy, mathematical and science competences, but also of 'softer' skills that firms need, such as communication or social abilities (Borras and Edquist, 2015). The last ones are becoming increasingly important within an organization, especially in fostering creativity and abilities of problems' solving (Lam, 2005). A study conducted by Davies, Fidler and Gorbis (2011) concluded that the 'soft skills' important for innovation are: sense-making in communication, social intelligence, novel and adaptive thinking, cross-cultural competency, computational thinking, new media literacy, trans-disciplinarity, new design mindsets, cognitive load management and virtual collaboration.

Two other important aspects for companies' innovative process are the quality and organization of vocational training and continuous skills development at the workplace (Brockmann, Clarke and Winch, 2011). The idea according to which there is a strong link between vocational training and innovation is widely accepted (Makkonen and Lin 2012; OECD, 2011). The findings of several researches underline that the vocational training is influenced not only by the relations between employee and employer, but also by the connections between the business and political environment (Harhoff and Kane, 1997; Culpepper and Thelen, 2008). Depending on the success of these relations, the vocational training may have different impacts on innovation's performance (Bosch and Charest, 2008).

Other studies suggest that the relationship between the vocational training and the innovation performance is mediated by many complex dimensions. For example, the continuous skills' acquisition is largely influenced by the development of firm specific competences (Smith et al., 2012). Moreover, it is also important that the skills' development stimulates the creativity and the innovative activities within the firm (Høyrup, 2010). Another research underlines the importance of the national institutional environment in promoting the creativity (Lorenz and Lundvall, 2011). Lorenz and Lundvall (2011) find a positive link between the creativity at work and the development of a competence-based system of education and the labor market flexicurity.

A large debate took place among researchers, business men and policy makers regarding the policies designed to stimulate the innovation and, recently, particular attention was paid to the development of competence building at the working place. Jones and Grimshaw (2012) underline that the efficiency of the policy schemes for vocational training can be noticed in the firms' innovative performance.

Knowledge, together with skills and experience define the 'competences' (Borras and Edquist, 2015). According to Borras and Edquist (2015), these may be 'core competencies', 'dynamic capabilities' and 'absorptive capacity'. Despite the fact that the literature underlines their importance in the innovation process, especially of those developed during formal education and training, some studies found that the effect of absorptive capacity on the innovativeness of a firm is positive only up to a certain level. When the companies are too dependent on external sources of knowledge, they tend to be less innovative (Laursen and Salter, 2006). Therefore, innovation is of a central importance to entrepreneurship (Covin and Miles, 1999), especially when it is the primary instrument of competition for a company (Baumol, 2002).

While the impact of the attracted FDI on firms' productivity and on the economic growth has largely been investigated, the effect of these investments on innovation has received less attention. Yet, the existing empirical studies suggest that the impact of the foreign firms on the innovation process in the host economy results from the technological spill-over and from the pro-competitive effect they generate. Multinational companies are considered an important channel of technology transfer due to the knowledge transmission through the vertical and horizontal linkages between them and the domestic firms (Blomström and Kokko 1998). However, technology spill-over will depend on the capacity of the local firms to implement the new technologies (Antonietti, Bronzini and Cainelli, 2015).

Taymaz and Lenger (2004), analyzing the Turkish manufacturing industries, concluded that foreign firms are more innovative than their domestic counterparts and they are able to transfer the technology. Sivalogathasan and Wu (2014) investigated the international technology spillover effect on domestic innovation capability for a sample of emerging South Asian markets, between 2000 and 2010. Their findings showed that the impact of FDI inflow on innovation is positive for all the analyzed states, confirming the hypothesis that the attracted foreign investments lead to knowledge and technology spillovers into the host country, and enhance regional innovation capacity and efficiency. Yet, the impact of this positive effect depends on the absorptive ability of the host region. Even though Sivalogathasan and Wu (2014) rejected the hypothesis of a crowding-out effect of FDI on innovation, other studies argued that some domestic firms may prefer obtaining the technologies from joint ventures agreements and, consequently, being less motivated to innovate (Cheung and Lin, 2004). However, this substitute for innovation is more attractive when conducting one's own research and development activity is risky or when the technology is of high standard (Lin, 2002). Cheung and Lin (2004) mentioned that, even when technology is obtained through FDI, the spillover effects to local firms could still occur. Hu and Jefferson (2001) bring the example of China, noting that the attracted FDI stimulated the research and development activity of the Chinese firms through different spillover channels. Therefore, it is likely that both the crowding-out and spillover effects co-exit.

Cheung and Lin (2004) stated that the presence of foreign goods in the domestic markets can encourage local companies to create blueprints for new products and processes. Therefore, the main motivation of developing countries to attract FDI is to obtain advanced technology that will help them establish domestic innovation capability. The extent to which spillovers can take place depends on both the owner of the advanced technology and the local enterprises (Narula and Marin, 2003).

Despite the fact that some analysts argued that FDI may also lead to negative spillover effects because of the competition (Aitken & Harrison, 1999), most of the researchers agreed that the attracted foreign investments can have a pro-competitive effect on the host economy. The foreign firms stimulate the competition in the local market because they force the local companies to search for innovative processes to increase their productivity (Keller, 2009). Yet, if the resources allocated for innovation do not have the expected results, the FDI might also have negative effects (Kiriyama, 2012).

Starting from the idea that FDI inflows help to promote local innovation capability, several researchers indicated that policies targeted at attracting FDI could improve the competitiveness of local markets (Antonietti, Bronzini and Cainelli, 2015). Moreover, the governments of the developing countries should strengthen the protection of intellectual property rights to encourage the innovation and guide the domestic firms to expand their innovative abilities (Sivalogathasan and Wu, 2014).

Several studies indicated the positive impact of foreign investors on the innovative process in different states. Bertschek (1995) and Blind and Jungmittag (2004) argued the impact of FDI on innovation in manufacturing and service firms from Germany. Aghion et al. (2009) found a positive effect of multinationals on the number of UK domestic firms' patents in technologically advanced sectors. Similar conclusions were drawn by Brambilla, Hale and Long (2009) on the case of the domestic Chinese firms, which were stimulated to innovate in the presence of foreign companies. Another study conducted on China by (Cheung and Lin, 2004), between 1995 and 2000, also found a positive impact of FDI on the number of domestic patent applications. In Europe, the positive impact of FDI on the innovation process of the domestic firms from the same industry was proven by Vahter (2011) on the case of Estonia and by Haskel, Pereira and Slaughter (2007) in the Central and Eastern European economies.

Antonietti, Bronzini and Cainelli (2015) tested the impact of the foreign investments on the innovativeness of the Italian companies through the two mechanisms: technology transfers and pro-competitive effects. Their results show that a higher level of inward FDI in services leads to a higher local patenting activity in knowledge-intensive business services. Yet, their results do not indicate that patenting in manufacturing is influenced by the presence of foreign firms. As confirmed by other studies, in manufacturing, innovation depends on urbanization economies (Carlino, Chatterjee and Hunt, 2007).

Some empirical studies underlined that companies innovate more when they are exposed to an increased low-cost import competition (Bloom, Draca and Van Reenen, 2011). The explanation for this fact is related to the opportunity cost of the inputs that firms use to innovate. Since the social return of innovation is higher than the private benefit, trade liberalization leads to a higher welfare. The increased import competition from low-cost countries gives local companies two options: to innovate or die (Bloom et al., 2013). Empirical studies confirmed this situation. For example, Bartel, Ichinowski and Shaw (2007) noticed that the US valve manufacturers, after losing the market for low-cost valves to Chinese competitors, started to invent smaller runs of innovative valves. A research conducted on 12 European countries by Bloom, Draca and Van Reenen (2011) reveal similar results. The European firms that faced an increased import competition from the Chinese companies invested more in research and development activities and in patenting. Therefore, the companies more threatened by the import competition had the largest increase in innovation. This behavior is confirmed by the dynamic general equilibrium model, which shows that adversity can increase the innovation if factors of production are kept inside the company (Bloom, Schankerman and Van Reenen, 2013).

Bloom et al. (2013) developed a model of endogenous growth and trade, with the help of which they argued that increased low-cost import competition stimulated the innovation of the domestic companies. Similar conclusions were drawn by Nguyen et al. (2011), who found positive spill-over from importing to non-importing firms: as importing companies become more productive, they can transfer their benefits to other firms by selling their goods along the vertical production chain. Yet, as mentioned by Pack (1992), if the development strategy of a country is based on nonselective import substitution that does not consider the economic efficiency, the innovation activities have very high opportunity costs and, therefore, reduce the competitiveness of the domestic companies. An example for this fact is brought by (Pamukcu, 2003) on the case of the developing states which, during the 1960s and 1970s, did not have innovation activities able to increase their productivity. Yet, he found positive effects of trade liberalization on innovation in the case of Turkish manufacturing industry, between 1989 and 1993.

Despite these situations in which imports do not necessarily lead to innovation, many researchers agreed that trade liberalization positively influences innovation due to improved market access and increased competition (Acemoglu and Linn, 2004; Bustos, 2011). Improved market access allows higher profits for the domestic companies, which, therefore, will have financial resources for innovation. A more competitive market forces the domestic firms to innovate in order to have better results than the competitors (Aghion et al., 2005). Related to this aspect, Aghion et al. (2016) bring strong empirical support to the idea that patent weights are highly correlated with sales weights. Moreover, some studies point to the fact that, in order to reap the benefits of trade liberalization, complementary policies should be implemented (Hoekman and Javorcik, 2004). The presence or absence of proper policies led to different results in terms of innovation and productivity. For example, while Tybout, De Melo and Corbo (1991) concluded that the innovation and productivity did not increase after the liberalization in Chile, Harrison (1994), Tybout and Westbrook (1995), Pavcnik (2002), Fernandes (2007) and Muendler (2004) noticed a positive impact of trade liberalization on innovation and productivity in Côte d'Ivoire, Mexico, Chile, Colombia and, respectively, Brazil. In the case of the developed countries, Bernard and Jensen (2001) did not find evidence that exporting raises the productivity and innovation of U.S. manufacturing plants. Opposite results were obtained by Baldwin and Gu (2003) on the case of Canada.

Some studies argued that trade facilitates the transfer of knowledge and best practices across countries (Grossman and Helpman, 1991). The implementation of the new technologies depends, however, on the absorptive capacities of the domestic firms that allow them to take advantage of the productivity gains associated with innovation (Cohen and Levinthal, 1990).

Starting from the assumption that many ideas for innovations come from foreign customers (Baldwin and Hanel, 2003), Baldwin and Gu (2004) investigated the innovative capacity of the Canadian manufacturing firms during the period 1984-1996. Their analysis revealed that exports facilitate the knowledge transfer across countries and stimulate the innovation process in Canada. This conclusion is supported through three major results: exports increased the use of foreign technology in domestic firms, stimulated the research and development agreements with foreign buyers and improved the flow of information about foreign technologies and innovations.

Coelli, Moxnes and Ulltveit-Moe (2016) analyzed the effect of trade policy on innovation during the Great Liberalization of the 1990s in more than 60 countries. By using international firm-level patent data, they proved that trade liberalization had a significant impact on innovation, technological change and growth. Moreover, they explain that the increase in patenting reflects more the level of innovation than higher protection of the existing knowledge. Coelli, Moxnes and Ulltveit-Moe (2016) explain their positive results on innovation through improved market access and higher import competition, in the context of trade liberalization.

Focusing on the effects of trade liberalization on innovation activities of small and medium size enterprises in Vietnam, Nguyen et al. (2011) mentioned that innovation, measured through new products, new processes or improvements in the existing products, is strongly influenced by trade liberalization. Their main conclusion was that globalization brought to Vietnam not only opportunities but also pressures for domestic firms to innovate in order to increase their competitiveness.

3. Data and Econometric Methodology

In the study, the impact of trade liberalization, FDI inflows and education on innovation was explored on the sample of 20 emerging market economies, during the 1995-2017 period.

3.1. Data

The innovation level was proxied by the number of total patent grants, due to the fact that Global Innovation Index, calculated through collaboration between Cornell University, INSEAD, and the World Intellectual Property Organization (WIPO), was available only for a limited period. Meanwhile, the trade liberalization was represented by the sum of exports and imports, and the FDI inflows were the foreign direct investment, in net inflows. Lastly, the education level was proxied by the education index of UNDP (United Nations Development Programme) (2019), calculated as mean of years of schooling for adults aged 25 years and more, and expected years of schooling for children of school entering age. All these variables used in the econometric analysis are presented in Table 1.

Table 1. Variables used in the econometric analysis.

Variables	Symbols	Source
Innovation proxied by total patent grants	INOV	World Intellectual Property Organization (WIPO) (2019)
Trade liberalization proxied by sum of export and import (% of GDP)	TRADE	World Bank (2019a)
Foreign direct investment, net inflows (% of GDP)	FDI	World Bank (2019b)
Education proxied by education index of UNDP	EDU	UNDP (2019)

The study sample consisted of 20 emerging market economies that experienced significant improvements in innovation, considering MSCI's (2019) classification. Therefore, the sample included Argentina, Chile, China, Colombia, the Czech Republic, Egypt, Greece, Hungary, India, the Korean Republic, Malaysia, Mexico, Pakistan, Peru, Philippines, Poland, Russia, South Africa, Thailand and Turkey. Brazil, Indonesia, Qatar, Saudi Arabia, Taiwan and the United Arab Emirates were not considered in the analysis. Furthermore, taking into account the availability of the data, the investigated period was 1995-2017. The econometric analyses were performed with the help of Stata 14.0, EViews 10.0 and Gauss 10.0 statistical software.

The summary characteristics and the correlation matrix of the dataset are presented in Table 2. As it can be noticed, the mean of the patent grants was 12451.69, and the total trade volume as a percent of GDP was 69.86% for the sample, but both figures changed considerably among the countries. Furthermore, the mean of FDI net inflows as a percent of GDP was about 3.08. Lastly, a positive correlation between innovation and trade liberalization, education and FDI inflows was noticed.

Table 2. Summary characteristics of the dataset.

	INNOV	**TRADE**	**FDI**	**EDU**
Mean	12541.69	69.86691	3.083648	0.645437
Median	1311.500	55.74130	2.346794	0.653000
Maximum	420144.0	220.4074	54.86819	0.893000
Minimum	65.00000	19.77142	-15.98922	0.232000
Std. Dev.	42008.50	41.28241	4.647363	0.140544
Correlation matrix				
	INNOV	**TRADE**	**FDI**	**EDU**
INNOV	1.000000	0.137748	0.253352	0.116552
TRADE		1.000000	0.231810	0.337229
FDI			1.000000	0.154947
EDU				1.000000

3.2. Econometric Methodology

In the applied section of the article, causality and cointegration relationships between innovation, trade liberalization, FDI inflows and education were analyzed with the help of the Westerlund and Edgerton (2007) LM bootstrap panel cointegration test and the Dumitrescu and Hurlin (2012) causality test, considering the pretests' results.

In this context, first cross-sectional dependence and homogeneity pretests were applied. Subsequently, the stationarity of the variables was analyzed with the Pesaran (2007) CIPS unit root test. Cointegration and causality analyses were conducted after stationarity analysis.

The Westerlund and Edgerton (2007) panel bootstrap cointegration test, which rests upon the lagrange multiplier test of McCoskey and Kao (1998), takes cognizance of cross-sectional dependency and heterogeneity, and produces reliable consequences in a state of small samples. The statistics of the test can be summarized in the following equation:

$$\boldsymbol{LM_N^+ = \frac{1}{NT^2}\sum_{i=1}^{N}\sum_{i=1}^{T}\widehat{w}_i^2 s_{it}^2} \tag{1}$$

In equation (1), the partial sums of error terms ($\boldsymbol{s_{it}^2}$) and long term variances ($\boldsymbol{\widehat{w}_i^2}$) are derived from the projected cointegration model with fully modified ordinary least squares. The critical values calculated from bootstrapping are considered in the case of cross-sectional dependency.

The causal interaction between innovation, trade liberalization, FDI inflows and education was tested with the Dumitrescu and Hurlin's (2012) test. The test considers the heterogeneity among the cross-sections, and yields robust results under the presence of cross-sectional dependence. The Dumitrescu and Hurlin's (2012) causality test can be used in the case of cointegration relationship's existence or non-existence. The model for the causality analysis is designed for the stationary variables of x and y as follows (Dumitrescu and Hurlin, 2012):

$$\boldsymbol{x_{i,t} = \alpha_i + \sum_{k=1}^{k}\gamma_i^{(k)}x_{i,t-k} + \sum_{k=1}^{k}\beta_i^{(k)}y_{i,t-k} + e_{i,t}} \tag{2}$$

$$\boldsymbol{y_{i,t} = \alpha_i + \sum_{k=1}^{k}\gamma_i^{(k)}y_{i,t-k} + \sum_{k=1}^{k}\beta_i^{(k)}x_{i,t-k} + e_{i,t}} \tag{3}$$

4. Empirical findings

The presence of cross-sectional dependence was tested with the LM CD test of Pesaran (2004) and $LM_{adj.}$ test of Pesaran et al. (2008), and the tests' results were presented in Table 3. The null hypothesis in favor of cross-sectional independence was rejected because the p values were found to be lower than 5%, and we reached the end of cross-sectional dependence among the cross-sections.

Table 3. Cross-sectional dependence tests' results (Null hypothesis: There is cross-sectional independence).

Test	Test statistic	p-value
LM (Breusch and Pagan (1980))	45.832	0.000
LM_{adj} (Pesaran et al. (2008))	39.671	0.013
LM CD (Pesaran (2004))	41.908	0.000

The homogeneity of slope coefficients was tested with the adjusted delta tilde test of Pesaran et al. (2008), and the tests' results are presented in Table 4. The null hypothesis asserting that the slope coefficients are homogeneous was rejected because the p values were found to be lower than 5%, and we revealed the heterogeneity of slope coefficients.

Table 4. Homogeneity tests' results (Null hypothesis: Slope coefficients are homogeneous).

Test	*Test statistic*	*p-value*
$\tilde{\Delta}$	9.367	0.002
$\tilde{\Delta}_{adj}$	10.342	0.000

We analyzed the stationarity with the help of the Pesaran (2007) CIPS test, regarding the presence of cross-sectional dependence among the series. The test results, presented in Table 5, indicate that all the variables were I (1).

Table 5. Homogeneity tests' results (Null hypothesis: The variable has unit root).

	Level		**First differences**	
Variables	**Constant**	**Constant + Trend**	**Constant**	**Constant + Trend**
INNOV	-0.941	-1.022	-7.453*	-9.459*
TRADE	-1.055	-1.178	-8.115*	-9.031*
FDI	-0.816	-0.971	-6.362	-8.362
EDU	-1.134	-1.165	-8.514	-9.114

* it is significant at 5% significance level

The long interaction between innovation, trade liberalization, FDI inflows and education was tested with the Westerlund and Edgerton (2007) LM bootstrap panel cointegration test regarding the pretests' results. The test results are presented in Table 6. The null hypothesis in favor of cointegration relationship's presence was accepted for both models: constant and constant and trend.

Table 6. Cointegration test's results (Null hypothesis: There is cointegration relationship among the variables).

	Constant			**Constant + Trend**		
	Test statistic	Asymptotic p-value	Bootstrap p-value	Test statistic	Asymptotic p-value	Bootstrap p-value
LM_N^+	9.324	0.389	0.451	10.389	0.378	0.467

Note: Bootstrap probability values were derived from 10.000 repetitive simulations and asymptotic probability values were derived from standard normal distribution. Lag and lead values were taken as 1.

The cointegration coefficients were estimated by FMOLS (Full Modified Ordinary Least Squares), regarding heterogeneity after specification of significant cointegration relationship between innovation, on one hand, and trade liberalization, FDI inflows and education, on the other hand. The panel cointegration coefficients revealed that FDI inflows had the largest impact on the innovation, with 21.5%, followed by education, with 19.8%, and trade liberalization, with 13.2%. However, the individual cointegration coefficients showed that the long term impact of trade liberalization, FDI inflows and education on the innovation varied from one country to another. However, both FDI inflows and education had no significant effects on the innovation in Pakistan, Peru and Philippines.

Table 7. Cointegration coefficients' estimation.

Countries	Coefficients		
	TRADE	FDI	EDU
Argentina	0.137*	0.197*	0.114*
Chile	0.108*	0.153*	0.186*
China	0.099*	0.231*	0.218*
Colombia	0.142*	0.196*	0.185
Czechia	0.105*	0.218*	0.153*
Egypt	0.136*	0.187*	0.166*
Greece	0.148*	0.206*	0.254*
Hungary	0.155*	0.223*	0.312*
India	0.167*	0.234*	0.273*
Korea Republic	0.189*	0.272*	0.289*
Malaysia	0.158	0.194*	0.041
Mexico	0.125*	0.161*	0.182*
Pakistan	0.103*	0.105	0.149
Peru	0.118*	0.196	0.156
Philippines	0.130*	0.103	0.163
Poland	0.129*	0.274*	0.258*
Russia	0.295*	0.297*	0.384*
South Africa	0.141*	0.225*	0.288*
Thailand	0.091*	0.194*	0.261*
Turkey	0.107*	0.166*	0.153*
Panel	0.132*	0.215*	0.198*

* it is significant at 5% significance level

Our results have a large support in various theoretical and empirical studies. Sivalogathasan and Wu (2014) found out that the attracted foreign investments have a large impact on the domestic innovation capability in South Asian countries: a rise of 1% in FDI inflow determines a 40% increase in the number of patent applications. Cheung and Lin (2004) have also noticed that, in China, the foreign investors have a significant positive effect on innovation: a 1% increase in FDI leads to an augmentation of 0.27% in the number of the applications for patents. Analyzing the link between FDI and total factor productivity of the Chinese industrial sectors, Liu and Wang (2003) underline that FDI facilitates the adoption of advanced technologies, being an innovation's determinant for the domestic firms.

Despite the studies that reflect the high impact of FDI on innovation, other researches noticed that these positive consequences depend on the sectors that receive the investments and on the period of time. For example, Antonietti, Bronzini and Cainelli (2015) observed that inward FDI in the service sector increases the number of local patents of knowledge-intensive firms. Yet, they found no impact of FDI on innovation in the manufacturing activities. Meanwhile, Chen's (2007) study conducted on the case of China indicates that, in a short term, FDI has only a weak impact on regional innovation capability. Even if FDI might have a crowding-out effect on innovation in the short term, in the long run, strengthening the absorptive capacity of the domestic enterprises may improve the innovation abilities. Similar results were found by Sivalogathasan and Wu (2014) on the case of a sample of South Asian states. If, in a short period of time, FDI could have negative consequences on innovation, the long-term effects could be positive. Yet, they depend on the changes in trade liberalization and on government expenditure on education.

Trade liberalization has also positive and negative impacts on firms' innovative abilities (Nguyen et al., 2011). Taking the case of the emerging market economies, Girma, Greenaway and Kneller (2004) explain the impact of trade liberalization on the behavior of firms, arguing that trade will enhance a company's competitiveness through innovation.

In the case of education, there are various studies highlighting the high impact that it has on innovation. The conclusions of a study conducted on 145 technology entrepreneurs reveal that both general and specific human capital stocks are important for innovation (Marvel and Lumpkin, 2007).

Lastly, the causal interaction between innovation, on one hand, and trade liberalization, FDI inflows and education, on the other hand, was tested with Dumitrescu and Hurlin's (2012) causality test. The test results, presented in Table 8, revealed a bidirectional causality between innovation and trade liberalization, and a unidirectional causality from innovation to FDI inflows and from education to innovation.

Table 8. Causality tests' results (Null hypothesis: There is no causality).

Null hypothesis	Test	Test statistics	P values
TRADE ↛ INNOV	Whnc	8.431	0.001
	Zhnc	7.990	0.000
	Ztild	5.321	0.000
INNOV ↛ TRADE	Whnc	6.532	0.015
	Zhnc	7.345	0.003
	Ztild	7.055	0.000
FDI ↛ INNOV	Whnc	1.642	0.251
	Zhnc	2.071	0.174
	Ztild	2.162	0.139
INNOV ↛ FDI	Whnc	9.532	0.009
	Zhnc	8.551	0.026
	Ztild	8.673	0.008
EDU ↛ INNOV	Whnc	7.532	0.001
	Zhnc	6.808	0.000
	Ztild	8.263	0.004
INNOV ↛ EDU	Whnc	1.532	0.107
	Zhnc	1.855	0.134
	Ztild	1.521	0.231

The bidirectional relationship between innovation and trade liberalization was also confirmed by various studies. A study conducted on Canadian firms concluded that those companies that are innovators are more likely to enter the export markets (Baldwin and Gu, 2004). Meanwhile, this process develops their innovative capacity. Allowing more research and development agreements with foreign partners, the exports will increase the quality of innovation. The findings of Baldwin and Gu's (2004) research show that, by entering the export markets, Canadian producers increase both the number of the advanced technologies and their quality, changing, therefore, the efficiency of the innovation process.

Among the researchers who found positive impact of trade on innovation can also be mentioned Bustos (2011) and Lileeva and Trefler (2010), who argued that trade determines exporters to upgrade technology, or Teshima (2009), who found that, in the context of reduction in Mexican output tariffs, the innovative activity of Mexican firms increased.

The bidirectional relation between trade and innovation was also noticed in the case of Turkish firms. Pamukcu (2003) found out that, in Turkey, both exporters and importers are more likely to innovate than the other companies that do not have relations with external firms. Meanwhile, he noticed that innovation has a positive impact on the propensity to export.

Contrary to our results, most of the researches showed that FDI stimulates innovation. For example, Nguyen et al. (2011) underline that FDI enhances not only the regional innovation systems, but also the productivity of innovation in developing countries. This occurs because business associations with multinational companies offer important learning and innovating opportunities for the domestic firms. The multinationals could reduce the costs of innovation for the local companies, which, therefore, will increase their productivity (Helpman, 1999). Meanwhile, the foreign firms may force the domestic suppliers to improve the quality of their goods or services, being, thus, a catalyst for innovation. Various examples were brought in the case on Germany (Blind and Jungmittag, 2004), UK (Aghion et al., 2009), China (Brambilla, Hale and Long, 2009) and Central and Eastern European economies (Haskel, Pereira and Slaughter (2007).

The impact of education on innovation has a large support in the literature. A study conducted by Nielsen (2006) reveals that having employees with a graduate degree may positively influence the propensity to innovate. This was noticed especially in small and medium-size firms from the IT sector (Vinding, 2004).

5. Conclusions

Innovation has been considered an important determinant of the competitiveness of both nations and firms. Unfortunately, the developing countries face various obstacles to innovate, many of them deriving from inappropriate business and governance environment, and insufficient education. Therefore, it is necessary for the policy makers to address these issues. As proven by various empirical studies, a first step towards a higher level of innovation would be opening the markets to trade and FDI, and investing in education.

Several studies conducted in different countries have underlined the idea according to which the role of the domestic firms in the developing states in creating new technologies is marginal. Yet, they will be able to innovate if they have money required for education, and if they face external stimuli, such as increased competition from the multinational companies. The increased foreign competition will force the domestic firms to improve their productivity by adopting more innovative technologies. Moreover, exports will increase the international exposure and, thus, they may lead to new knowledge accumulation.

Considering all the empirical and theoretical evidence offered by the literature, we may argue that foreign competition, coming both from trade and FDI, is related to high innovation, fast productivity growth and, therefore, economic prosperity at the micro and macro levels.

Meanwhile, education offers people the proper tools to become more creative and for coming up with new ideas.

Starting from these assumptions, our research revealed that FDI, together with trade and education, have an important impact on the innovation process of the analyzed emerging economies. Yet, FDI inflows and education had no significant effects on the innovation in three states: Pakistan, Peru and Philippines. For the rest of the sample, FDI seems to have the largest impact, closely followed by education. We also found out that the long-term effects vary from one country to another.

The direction of the relations between innovation and the three analyzed determinants proved to be bidirectional in the case of trade liberalization, and unidirectional in the case of education and FDI. Our findings showed that, while education stimulates the innovation, in the case of FDI, it is influenced by innovation.

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