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The Impact of Innovation on High Technology Exports in South Korea, Germany and United States: New Evidence

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Abstract

This study aimed to test the impact of innovation on high-tech exports in South Korea, Germany, and the United States. Annual data were tested over the period 1988-2023. Autoregressive distributed lag (ARDL) was used, the results indicated the existence of cointegration between the study variables for the three countries. The long-run outcome showed that high-tech exports in both South Korea and Germany were positively significant affected by patents. In the short run, high-tech exports were positively significant affected by patents in South Korea, Germany, and the United States. Surprisingly, research and development (R&D) spending affects South Korea's exports, but it is not statistically significant in the short run, despite the high spending rates. Conversely, high-tech exports in Germany and the United States were positively and statistically significant affected by R&D spending. Finally, the results showed that both foreign investment and gross fixed capital formation affect high-tech exports.

Keywords: Innovation, High Technology, Exports, South Korea, Germany, USA

JEL Calcification: M16, O30, O31, O38

Introduction

Endogenous growth theory suggests that the adaptation of technology, along with innovation and imitation, are crucial elements for a nation's technological advancement (Romer, 1990). This advancement plays a role in an economy's growth by influencing its competitive stance in international markets. Vernon (1966) highlights the significance of technological factors in global competition, which stem from the unique advantages of countries, leading to the creation of new products and processes. Research often treats innovation as an external factor and posits that it influences a country's export efficiency (Krugman, 1979; Posner, 1961).

In recent years, the world has witnessed tremendous developments in the field of information and communications flows, accompanied by significant advances in technology. The collapse of international borders in the face of growing international trade and the emergence of global homogeneity of tastes has contributed to a transformation in the global economy. Innovation has become a feature of everyday life, and modern technology has become a primary goal of major economies. The forces of globalization have enhanced global innovation by creating high-tech products in the home country and redistributing them to international markets (Leonidou and Katsikeas 2010).

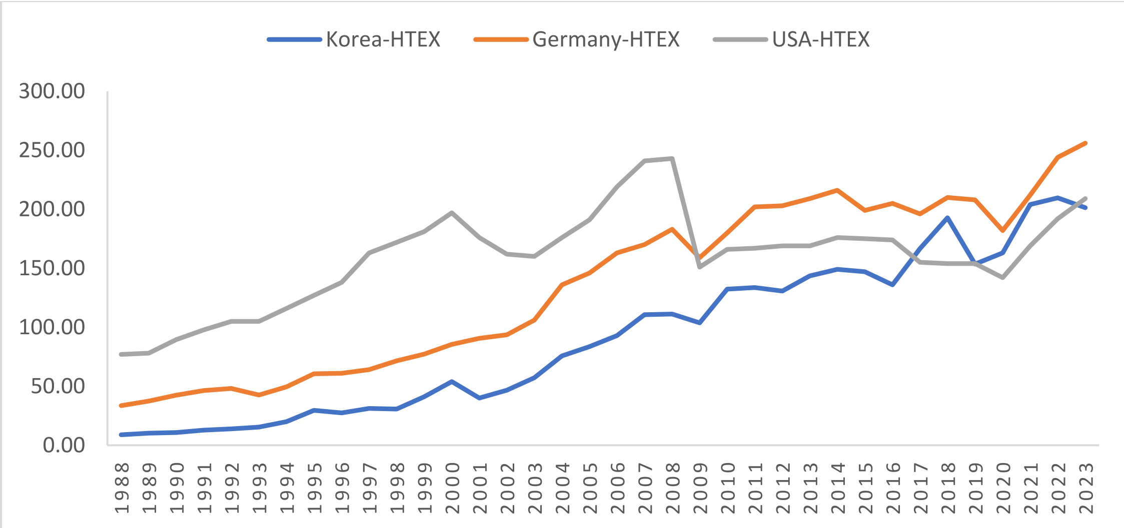
Traditionally, it has been assumed that the export structure of countries relied heavily on the proportion of ownership of production factors. This has led developed countries to specialize in high-tech products. Specialization leads to efficient resource management, which is reflected in competitiveness in terms of price and quality. Thus, innovation contributes to enhancing competitive advantage by reducing costs and developing new products with high efficiency that attract new customers. High-tech exports are characterized by their dynamic component, which makes innovation highly linked to trade activities especially in advanced technology equipment's. This creates a bidirectional relationship between innovation and technology exports (Smallbone et al. 2022).

Technological innovation can be described as a nation's "absorption capacity"—the capability to implement outside information by creating new products and processes that are essential for global trade and economic growth (Zahra and George, 2002). Innovative activities are scientific, technological, financial, and institutional fields that contribute to changing traditional production patterns and imbuing the economy with an innovative character. Patents are the fruit of innovation and an indicator of the performance of development processes in the economy. They reflect the success of allocating research and development within highly productive activities (Crosby, 2000).

Innovation can provide a competitive advantage by focusing on costs, by developing a new, more efficient production process, and/or by building differentiation through product innovations, which allow companies to customize their products to customer requirements, or develop higher-quality products. (Lopez Rodriguez and Garcia Rodriguez, 2005). High-tech exports contribute to long-term economic growth sustainability compared to traditional industries. This is because high-tech products tend to be income-elastic, leading to the creation of new demand, replacing old ones, and accelerating international trade (Montobbio & Rampa, 2005).

Global high-tech exports reached approximately $1.969 trillion in 2007, with South Korea, Germany, and the United States accounting for the largest share. These exports continued to grow, reaching approximately $3.754 trillion in 2023. South Korea's high-tech exports in 1988 was 8.91 billion USD gradually increased until they reached 201.27 Billion USD in 2023, Germany's high-tech exports in 1988 was 33.6 billion USD continued to increase until they reached 256 billion USD in 2023, the United States' high -tech exports in 988 was 77 billion USD continued to increase until they reached 209 billion USD, The figure 1 shows the trend of development high-tech exports in South Korea, Germany, and the United States.

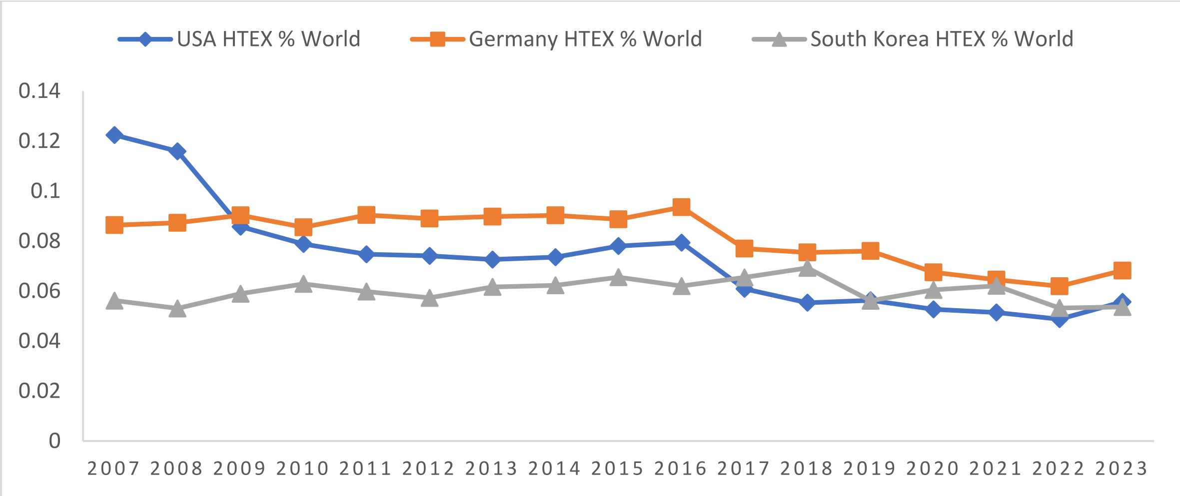
Figure 1. South Korea, Germany and United States High-Technology Exports trend (1988-2023) In Billion USD



Source: World Bank, OCED

Regarding the share of South Korea, Germany, and the United States high technology exports in globally. In 2007 the South Korea share was 6%, this decline to 5% in 2023. In 2007 Germany share was 9%, this decline to 7% in 2023. In 2007 the United States share was 12% sharply dropped to 6% in 2023. This decline in share for these countries is due to the fact that many countries have achieved significant growth in high-tech exports, such as China, whose exports peaked in 2021, recording $936.39 billion, and its share of the global market for high-tech exports was 28.5%. Figure 2 show the South Korea, Germany and USA High-Technology Exports % World.

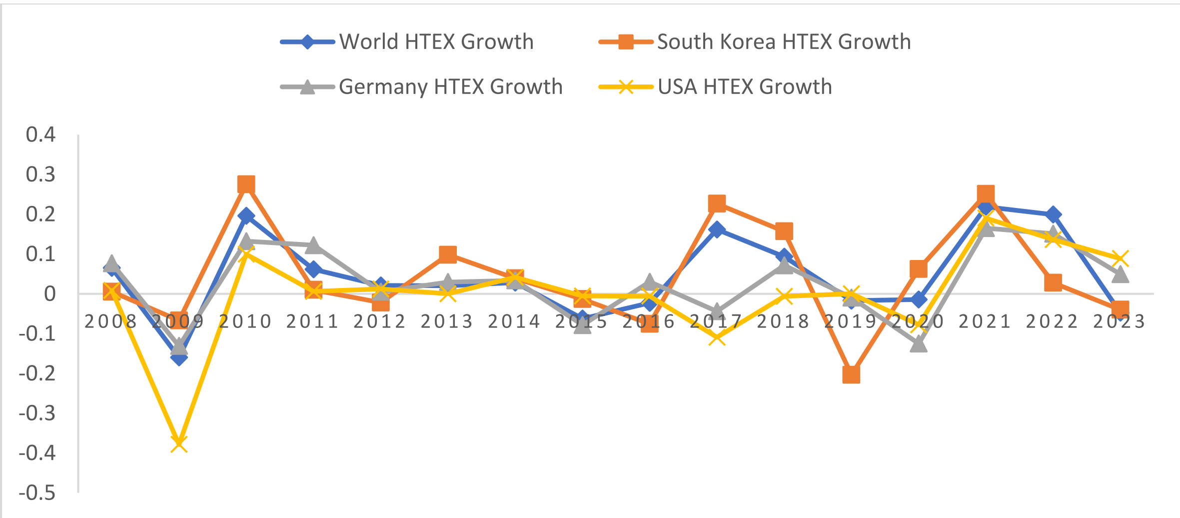
Figure 2. South Korea, Germany and USA High-Technology Exports % World



Source: World Bank

The worldwide growth rate of high technology exports in 2008 was 6%, In 2023 declined by 5%. The growth rate of high technology exports in 2008 was 1%, declined by 2023 4% in South Korea. In Germany the growth rate of high technology exports in 2008 was 8%, declined to 5% in 2023. Interestingly, in the United States the growth rate of high technology exports in 2008 was 1%, boosted to 9% in 2023. Figure 3 illustrates the growth trend in high-tech exports in the three countries compared to the global growth.

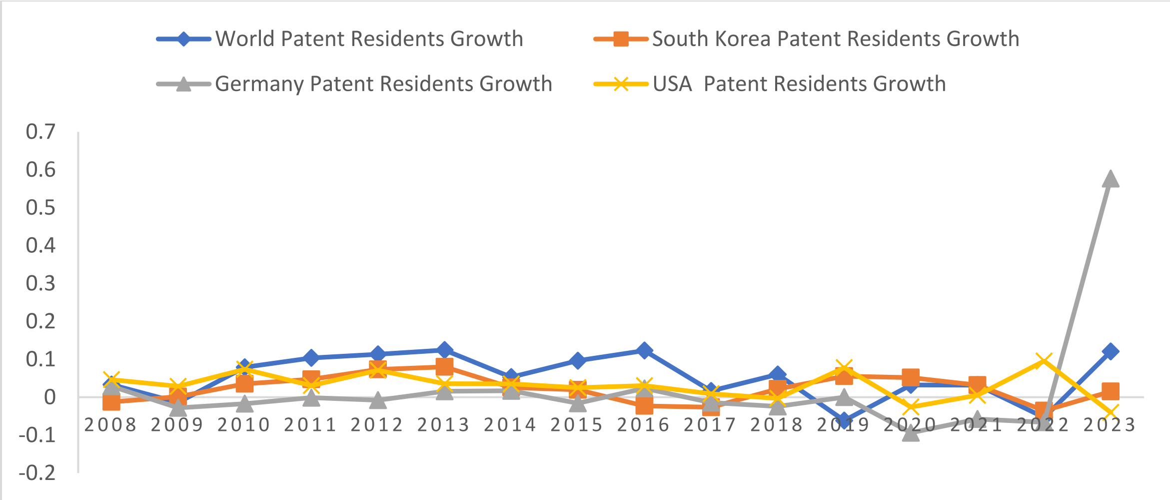
Figure 3. World, South Korea, Germany and United States High-Technology Exports trend growth (2008-2023)



Source: World Bank

Global patent growth in 2008 was approximately 3%, and in 2023 it reached 12%. Regarding patent growth in South Korea in 2008 declined by 1.2%, by the end of 2023 recorded growth reached to 1.5%. in Germany the patent growth was 3%, remarkably recorded 57% in 2023. Finally, in the United States the patent growth was 5 % in 2008, and by 2023 declined to 5%. Figure 4 show the Patents resident trend growth in the World, South Korea, Germany and USA during (2008-2023).

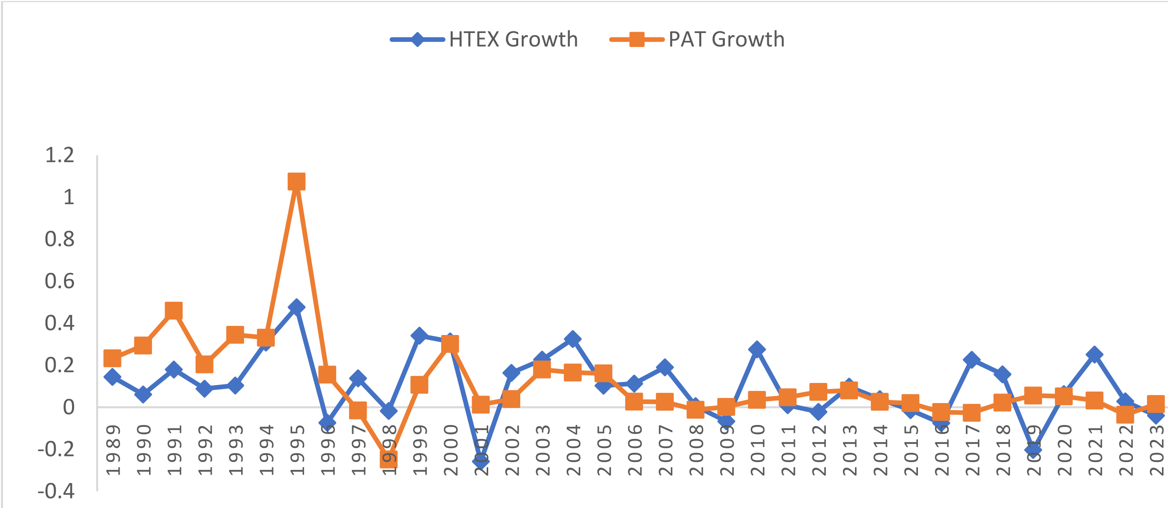
Figure 4. Patents resident trend growth in the World, South Korea, Germany and USA (2008-2023)



Source: World Bank

South Korea experienced significant growth in patents in the early 1990s, with growth peaking in 1989 at approximately 23%. In 1995, there was a meteoric growth reaching approximately 107%. After that, the growth rate continued to fluctuate and by 2023 reached 2%. Where the growth in high-tech exports recorded 14% in 1989. In 1995 there was a significant growth reaching approximately 47%. By the end of 2023 declined to 4%. The average growth in patents and high-tech exports was 12% and 10%, respectively. Figure 5 shows the growth in patents and Korean high-tech industries during the period 1989-2023.

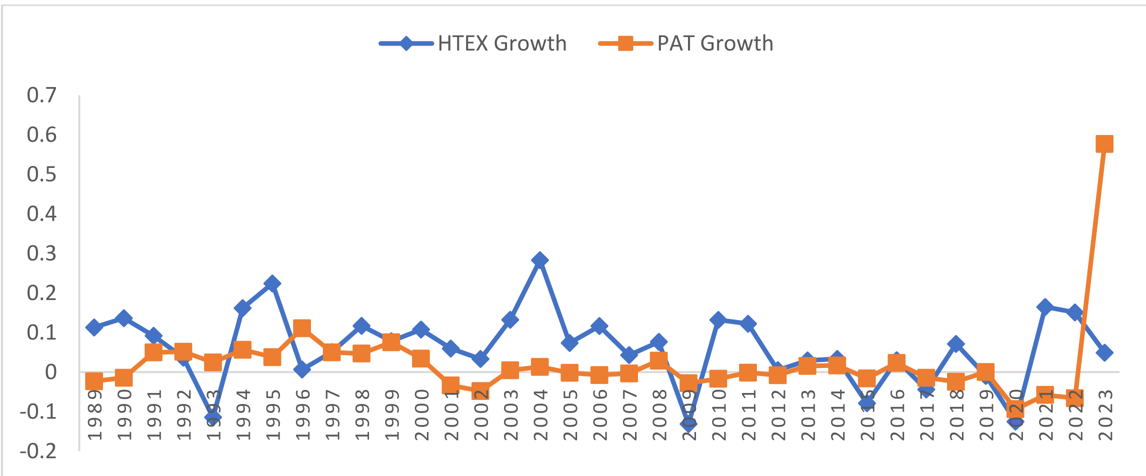
Figure 5. Growth of South Korea patents of resident and High-Technology Exports (1989-2023)



Source: World Bank, OCED

According to Figure 6 the growth of patents in Germany in 1989 declined 2%, continued to up and down until 2022, in 2023 the growth rate of patents grew significantly and recorded 57%. On the other side, the growth in high-tech exports during the period 1989-2023 was 11% in 1989 and 5% in 2023, with an average growth of 2% for patents and 6% for high-tech exports. Figure 6 shows the growth rate of German patents and high-tech exports during the period 1989-2023.

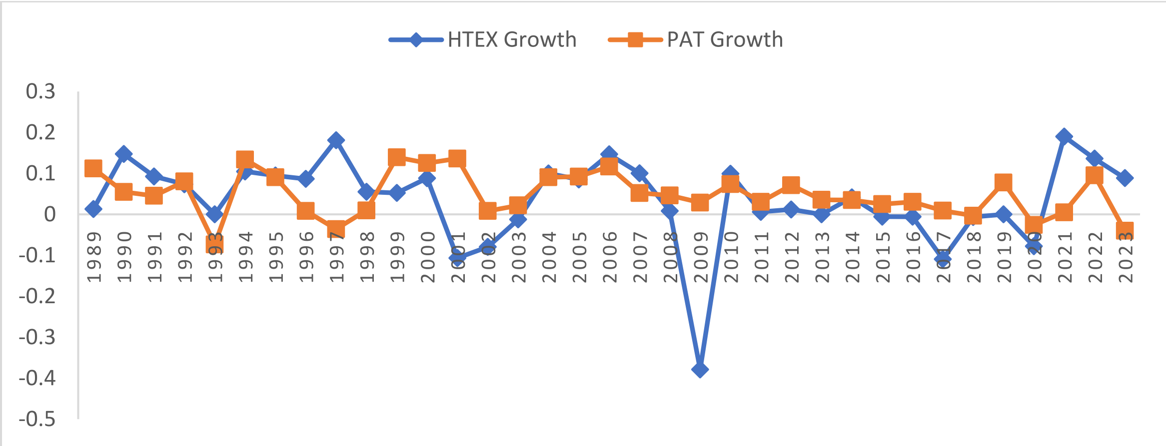
Figure 6. Growth of Germany patents of resident and High-Technology Exports (1989-2023)



Source: World Bank, OCED

Finally, the growth of patents in the United States in 1989 was 11%, continued to up and down recoded decline by 4% in 2023.The United States is making great efforts to increase its high-tech exports. In 1989, the growth rate of high technology exports was 1.3% continued to fluctuate between high and low until 2009 which recorded sharp decline and then reached 37%. as a result of the global financial crisis, after that, it rose again and still fluctuate until 2023 which reached to 8%. The average growth in patents and high-tech exports during the period 1989-2023 was 3% and 5%, respectively. Figure 7 shows the growth trend in patents and high-tech exports in the United States during the period 1989-2023.

Figure 7. Growth of United States patents of resident and High-Technology Exports (1989-2023)



Source: World Bank, OCED

In this study, the impact of innovation on high technology exports of the South Korea, Germany and united Sates for the period 1988-2023 were analyzed by using annual data. presented.

Literature review

Exports of high-tech products and advancements in innovation have received significant focus in recent years. Numerous studies have particularly highlighted the globalization process of high-tech companies and their innovative assets (Crick & Jones, 2000; Kelly et al., 2021; Aghion et al., 2022). Tebaldi (2011) has shown innovation is one of determinants of high-tech exports. Braunerhjelm and Thulin (2008) have revealed that R&D expenditure is an important determinant of high-tech exports.

D'Angelo (2012) studied how innovation affects the export intensity of small and medium-sized high-technology firms in Italy, utilizing a dataset with 3,452 observations that included a wide range of variables, encompassing both survey data and financial statements, analyzed through Tobit regression models. The findings indicate that employees involved in R&D have a positive and significant effect on the export intensity of high-technology SMEs, while R&D spending does not have the same impact; collaborating with 'Universities' as external R&D partners positively influences the export intensity of these firms; additionally, 'Product innovations' and the revenue generated from innovative activities significantly and positively correlate with export intensity.

Alemu (2013) examined the impact of R&D investments and the number of researchers on high-tech exports for the 1994–2010 period of 11 East Asian countries. The analysis using the panel GMM estimation method concludes that the R&D expenditures/GDP ratio and the rise in the number of R&D personnel increase high-tech exports. Sandu and Ciocanel (2014) investigated the relationship between medium and high-tech exports, and the main determinants of innovation, The data for 26 countries (all EU-27 countries, except for Luxembourg), along the 2006-2010 period have been extracted from the 2012 Innovation Union Scoreboard. The results confirm a causal relationship between the independent variables mentioned above and the EU high-tech exports level. Moreover, results also confirm a positive correlation between total R&D expenditure volume and the level of high-tech exports, with variability between countries. The influence of private R&D expenditure on high-tech exports is stronger than public R&D expenditure.

Ghanbari and Ahmadi (2016) inspected the effect of innovation on international trade. It examines the impact of R&D as a proxy of innovation on three medium high-tech industries exports in Iran, Japan, Korea and Australia using panel data method over a period from 2003 to 2012. Findings show that innovation has a positive and economically large effect on export performance of all industries. This suggests innovation is a central driver of trade. Bayraktutan and Bıdırdı (2018) investigated the effect of the number of patents on high and medium-high-tech export (HTEX) performance in developed and developing countries, panel co-integration methods separately for DC and LDC with the annual data of 16 DC and 10 LDC for the 1996–2012 period were used. Estimation results show that PAT (Patents of residents) is one of the key determinants of HTEX in both groups of countries and PAT elasticity of HTEX in developing countries is higher than that of developed ones. However, while there is no short-run causality from PAT to HTEX, there is short-run causality from GFC and FDI to HTEX.

Chalioti et al. (2020) studied the relationship between innovation, patents, and trade in Greece. The sample for the study includes the identities of exporting companies, their export characteristics, and their patent application activity from 2005 to 2007. The findings indicate that patents have a positive effect on export volume, and that innovative firms tend to export more than their non-innovative competitors, particularly in more remote markets. Panda and Sharma (2022) utilizing a meta-regression analysis, examines the impact of innovation on export performances. a meta-analysis from 27 empirical studies that contain 249 estimates undertaken during 1996–2019 used. Study findings show that developed countries' domestic innovation enhance their exports; however, for developing countries, innovation does not contribute to their exports. Tandrayen-Ragoobur (2022) investigates the relationship between innovation and export behaviour across manufacturing and services firms in Africa. Using data from 45 African countries, from 2006 to 2020, the multinomial probit and two-stage least squares models are estimated. There is support for the learning by exporting and the self-selection hypotheses for African firms. The findings reveal the need to improve the business environment across African economies to foster greater exports and innovation.

Recently, Zaman and Tanewski (2023) examined the "learning to export" and "learning by exporting" hypotheses in SMEs and large firms in Australia, Financial data are derived from the Australian Tax Office's (ATO), Business Income Tax (BIT), between 2001-2002, and 2018-2019. Using instrumental variable (IV) regressions and path analyses, the empirical assessment provides evidence that R&D and innovation should be regarded as two separate constructs. Results also revealed that there is a significant mediating effects between R&D and Export via Innovation and between Export and R&D via Innovation only in the large company cohort. SMEs do not show evidence of simultaneity among R&D, innovation, and exporting nor do the results provide support for the "learning by doing" hypothesis in SMEs. Moreover, Zapata et al. (2023) investigated the factors influencing high-tech exports, presenting new findings from a study of 35 OECD countries over a period of 15 years (2004 to 2018). They employed panel data estimation methods, the results suggest that research and development, inward foreign direct investment relative to GDP, gross fixed capital formation, and membership in the EU are key determinants of technology-intensive exports.

Model Specification Methodology, and Data

Model Specification

The study examines the impact of innovation on high -technology exports for South Korea, Germany, and united states. The variables analyzed in the study were chosen based on existing literature and aligned with economic theory. Thus, Following (Sandu and Ciocanel, 2014; Bayraktutan and Bıdırdı, 2018; Vlčková and Stuchlíková, 2021; Chalioti et al., 2020; Gocer, (2013; Bottega and Romero, 2021). The study model specified and presented in Eq. (1).

$$HEX = F(PAT, FDI, GFCF, RD) \quad (1)$$

Where HEX represents the high technology exports, PAT residents patent a proxy of innovation, Grilliches (1990), Greenhalgh et al. (1994), and Madsen (2008) contend that patents serve as the most reliable metric for assessing technology. Grilliches (1990, p. 1661) states that patents "are inherently connected to creativity and are founded on what seems to be a stable and objective standard." Patents can be quantified without inaccuracies and reflect the outcomes of both formal and informal research endeavors (Madsen, 2008). The existing literature also highlights a significant correlation between patent counts and R&D spending in a cross-sectional context (Grilliches, 1990; Greenhalgh et al., 1994; Madsen, 2008). This indicates that patents may effectively represent disparities in innovative activities among firms and/or nations. Additionally, Grilliches (1990) notes that although the tendency to patent differs across industries, the correlation between patents and R&D is nearly proportional. Most notably, patent data is generally more accessible than R&D data. Therefore, even though they are not perfect indicators of innovation, Grilliches (1990, p. 1700) remarked that "patent statistics continue to be a singular resource for examining the dynamics of technical advancement." FDI foreign direct investment, GFCF gross fixed capital formation, and *RD* research and development expenditure % of GDP.

By applying the natural logarithm to both sides of equation (2), estimation function become as follows:

$$LHEX = C + \beta LPAT + \alpha LFDI + \delta LGFCF + \gamma LRD + e \quad (2)$$

Where *ln* denotes natural logarithm, C represents a constant parameter, e is the error term, $\boldsymbol{\beta}, \boldsymbol{\alpha}, \boldsymbol{\delta}, \boldsymbol{\gamma}$,denote respectively constant elasticity coefficients signs are expected to be positive.

Methodology Estimation

This research utilizes the ARDL bounds testing method for cointegration introduced by Pesaran, Shin, and Smith (2001) to analyze the empirical connections between the study variables. The ARDL model provides reliable outcomes, especially when dealing with small sample sizes.

$$\Delta HEX = C + \eta LHEX_{t-1} + \beta LPAT_{t-1} + \alpha LFDI_{t-1} + \delta LGFCFp_{t-1} + \gamma LRD_{t-1} + + \sum_{i=1}^{p} \eta_2 LHEX_{t-i} + \sum_{i=0}^{p} \beta_2 LPAT_{t-i} + \sum_{i=0}^{p} \alpha_2 LFDI_{t-i} + \sum_{i=0}^{p} \delta_2 LGFCF_{t-i} + \sum_{i=0}^{p} \gamma_2 RD_{t-i} + \varepsilon_t \quad (3)$$

In this context, Δ denotes the first difference operator; C represents an intercept, ε_t error term, he long-run coefficients are labeled as $\eta, \beta, \alpha, \delta, \gamma, ,$ whereas $\eta_2, \beta_2, \alpha_2, \delta_2,\ \gamma_2,$ indicate the short-run coefficients that form the underlying ARDL model.

There are two steps involved in estimating the given model using the ARDL approach. ARDL Bounds testing begins with estimating the Equation (3) using the ordinary least square approach (optimal lags included). Subsequently, an F-test is conducted to assess the collective significance of the coefficients of the lagged levels of the variables being analyzed in the model. The F-test is used to determine if the variables of interest in Equation (3) have long-run cointegration interrelationships.
Two sets of critical values are created during the F-test for joint significance; these are known as the upper-bound critical values for the I(1) series and the lower-bound critical values for the I(0) series (Pesaran and Smith 1998). After that, if the computed F-statistic lies outside of the critical value bounds, a definitive conclusion about cointegrating relationships can be drawn by comparing the computed F-test statistic to the critical value bounds published by Pesaran, Shin, and Smith (2001). This procedure is the same as using the F-test statistic to assess the alternative hypothesis (H1) of cointegration versus the null hypothesis (H0) of no-level cointegration connection. Consequently,
$H_0 : \eta = \beta = \alpha = \delta = \gamma = 0$ is against $H_1 : \eta \neq \beta \neq \alpha \neq \delta \neq \gamma \neq 0$

To test the null hypothesis (H0) for cointegration against the alternative, if the calculated value of the F-statistic higher than the upper bound of critical values. The H0 cannot be rejected. If the F-statistic is less than the lower critical value bounds, we accept alternative hypothesis H1 option. However, conclusive inference is not possible when the calculated F-statistic falls between the higher and lower value ranges. After the cointegration relationship has been established, it is necessary to estimate the long-run coefficients of Equation (3). Subsequently, the short-run dynamics can be derived through the error-correction model (ECM) presented in Equation (4), which is outlined as follows:

$$\Delta HEX = C + + \sum_{i=1}^{p} \eta_2 LHEX_{t-i} + \sum_{i=0}^{p} \beta_2 LPAT_{t-i} + \sum_{i=0}^{p} \alpha_2 LFDI_{t-i} + \sum_{i=0}^{p} \delta_2 LGFCF_{t-i} + \sum_{i=0}^{p} \gamma_2 RD_{t-i} + \mu ECM_{t-i} + \varepsilon_t \quad (4)$$

Data

This study examines the impact of innovation on high-tech exports for South Korea, Germany and united states. Analysis data obtained from 1988 to 2023. Sources of data World Bank Database, OECD, WIPO, World Development Indicators, Ministry of Science and Technology (Korea), Science and Technology Annual 1993 (in Korean), Descriptive statistics Table 1. are utilized to present information on a selection of variables. The findings indicated that the mean values for all variables fall within the anticipated range, confirming the absence of extreme values in the dataset. Despite this, the calculated standard deviation for the analyzed parameters suggests a sufficient degree of volatility in the data. Furthermore, the data for all the parameters used shows negative skewness, with none of the skewness values exceeding the specified limits of +1 and −1. For all considerations, each parameter analyzed exhibits a normal distribution, as demonstrated by the Jarque-Bera statistic and its corresponding probability. Consequently, researchers were able to leverage the provided data for further analyses, including variable estimation and empirical investigations.

Table 1. Descriptive Statistics

	LOG(HEX)	LOG(RD)	LOG(PAT)	LOG(GFCF)	LOG(FDI)
South Korea					
Mean	4.138431	1.058356	11.23353	5.553434	-0.290923
Median	4.478587	0.962899	11.72659	5.663411	-0.231505
Maximum	5.345445	1.650580	12.13482	6.355252	0.768245
Minimum	2.187091	0.609766	8.647519	4.113227	-1.551351
Std. Dev.	0.996828	0.346393	1.000284	0.594409	0.577241
Skewness	-0.567836	0.317683	-1.301461	-0.508610	-0.310350
Kurtosis	1.980231	1.564376	3.553547	2.382772	2.621322
Jarque-Bera	3.494522	3.697060	10.62243	2.123559	0.792996
Probability	0.174251	0.157468	0.004936	0.345840	0.672672
Germany					
Mean	4.736637	0.961402	10.68393	6.400882	0.833185
Median	5.026255	0.958413	10.75825	6.397958	0.969383
Maximum	5.545177	1.202972	10.97945	6.880396	2.610697
Minimum	3.514526	0.741937	10.33280	5.773994	-1.257033
Std. Dev.	0.643100	0.131880	0.162826	0.282365	0.679787
Skewness	-0.485901	0.032874	-0.878825	-0.286808	-0.419693

Kurtosis	1.728950	1.898542	2.725868	2.379735	4.599767
Jarque-Bera	3.839950	1.826299	4.746720	1.070645	4.895736
Probability	0.146611	0.401258	0.093167	0.585481	0.086478
United States					
Mean	5.035022	0.994603	12.07643	10.16744	0.346510
Median	5.114991	0.962219	12.17164	10.21817	0.370553
Maximum	5.493061	1.243512	12.79559	10.99030	1.225474
Minimum	4.343805	0.832909	11.13669	9.373209	-0.766032
Std. Dev.	0.284027	0.106726	0.538413	0.465798	0.475873
Skewness	-0.905710	1.117529	-0.233069	-0.179563	-0.291184
Kurtosis	3.332656	3.438651	1.568049	2.031692	2.708532
Jarque-Bera	5.087851	7.781842	3.401652	1.599889	0.636161
Probability	0.078557	0.020427	0.182533	0.449354	0.727544

Empirical results

In Table 2, the findings of the optimal lag selection are displayed. Identifying the best lag in the ARDL model aims to address the issue of autocorrelation within the model system by treating the lag in endogenous variables as an exogenous variable. The optimal lag determination is based on the likelihood ratio (LR), final prediction error (FPE), AIC, Schwarz information criterion (SIC), and Hannan–Quin criterion (HQ) values. As indicated in Table 2, the chosen lag is lag 2 , 3, 4 regarding to South Korea, Germany, United States respectively. Selecting lag 2, 3, 4 as the optimal lag implies that all variables not only influence each other in the same period but also in the preceding two periods, three periods, four periods in south Korea Germany and USA.

Table 2 **lag selection**

South Korea						
Lag	**LogL**	**LR**	**FPE**	**AIC**	**SC**	**HQ**
0	-4.747762	NA	1.22e-06	0.573398	0.797863	0.649947
1	158.8574	269.4673	3.58e-10	-7.579844	-6.233056*	-7.120551*
2	189.4128	41.33978*	2.86e-10*	-7.906638*	-5.437525	-7.064600
Germany						
0	44.27030	NA	6.37e-08	-2.380018	-2.153274	-2.303726
1	197.1317	250.1369*	2.80e-11	-10.12919	-8.768733*	-9.671441*
2	223.1759	34.72565	2.94e-11	-10.19248	-7.698302	-9.353266
3	254.3733	32.14270	2.76e-11*	-10.56808*	-6.940180	-9.347400
United States						
0	64.58891	NA	1.66e-08	-3.724307	-3.495286	-3.648393
1	234.1302	275.5046*	2.03e-12*	-12.75814	-11.38401*	-12.30265*
2	256.8097	29.76681	2.65e-12	-12.61311	-10.09387	-11.77805
3	280.1239	23.31418	4.17e-12	-12.50774	-8.843402	-11.29312
4	320.3238	27.63748	3.61e-12	-13.45774*	-8.648294	-11.86354

Before engaging in cointegration, it is essential to perform unit root tests to assess the stationarity characteristics of the parameters and then conduct descriptive statistics to ensure normality. This step is vital as it aids in selecting an appropriate test for the subsequent phase of the study and identifies the type of stationarity of the parameters being analyzed. Two-unit root testing methods were implemented in this study. As shown in Table 3, all parameters evaluated displayed stability al level I(0) or after the first difference I(1). This indicates that cointegration and the ARDL estimator can be utilized with the data.

Table 3 The results of unit root tests

Variable	Augmented Dickey-Fuller		Phillips-Perron	
	At level	First difference	At level	First difference
		South Korea		
LOG(HEX)	-3.094990**	-5.800460***	-6.041087***	-6.404840***
LOG(RD)	0.293156	-4.260023***	0.294879	-4.175078***
LOG(GFCF)	-2.397531	-5.319329***	-2.463143	-5.386850***
LOG(FDI)	-2.766908*	-6.078349***	-2.286636	-7.990698***
LOG(PAT)	-8.495340***	-2.246927	-15.33504***	-3.408929**
		Germany		
LOG(HEX)	-1.779234	-5.470229***	-1.915708	-5.470229***
LOG(RD)	0.564516	-3.903786***	-0.226894	-2.967431**
LOG(GFCF)	-1.599231	-5.370647***	-1.598772	-5.370647***
LOG(FDI)	-3.915639***	-8.219739***	-3.879970***	-9.401636***
LOG(PAT)	-1.727242	-2.738657*	-1.447831	-2.084684
		United States		
LOG(HTEX)	-2.366835	-5.093943***	-2.388365	-5.097152***
LOG(RD)	-0.261542	-4.359353***	0.239443	-4.247688***
LOG(GFCF)	-0.281863	-3.943233***	-0.241444	-2.909200*
LOG(FDI)	-3.106302**	-7.248305***	-3.159991**	-9.372738***
LOG(PAT)	-2.067688	-5.478404***	-1.783604	-5.456986***

*, ** and ***, 1% , 5% and 10%

The dataset's stationarity can be assessed based on the results from the unit root tests. An ARDL bounds test was conducted to evaluate whether a cointegration relationship exists among the parameters utilized. The results of the cointegration analysis are presented in Table 4. The computed F-statistic for cointegration (9.32), (8.67), (4.99) regarding to South Korea, Germany, and United states respectively, exceeds the maximum permissible limit. This study identifies a cointegration relationship among the variables.

Table 4. ARDL Bounds Test Results

Null hypothesis: No degree of relationship

			South Korea	Germany	United states	Result
Signif.	I(0	I(1)				
10%	2.2	3.09				
5%	2.56	3.49	F = (9.32)	F = (8.678)	F = (4.991)	Cointegrated ***
2.5%	2.88	3.87	K 4	K 4	K 4	
1%	3.29	4.37				

*, ** and ***, 1% , 5% and 10%

The results of the long- and short-term tests showed that Korean high-tech exports had a positive impact on all variables. In the long-term, a 1% increase in patents contributes to a 43% increase in high-tech exports, while in the short-term, they increase by 22%. Foreign investment contributes to a 13% increase in exports with a 1% increase in the long term, and 8% in the short term. Fixed capital accumulation contributes 70% to high-tech exports with a 1% increase, meaning that a large portion of this accumulation finds its way into technology industries. In the German case, patents have a significant impact on high-tech exports, as a 1% increase in patents contributes to a 3.06% increase in exports in the long run and a 43% increase in the short run. Capital formation also has a positive impact on high-tech exports, as a 1% increase in patents contributes to a 1.27% increase in exports in the long run and a 52% increase in the short run. Spending on scientific research has a negative impact on high-tech exports, as a 1% increase in spending leads to a decrease in high-tech exports in the short run. This is because this spending has not led to an increase in labor productivity in high-tech industries (Naudé and Nagle, 2017). Finally, the results of the test in the US case showed that capital accumulation in the United States contributes approximately 1.28% to high-tech exports with a 1% increase in the long run. In the short run, high-tech exports increase by 44%, 2.61%, 9%, and 1.7% when patents, fixed capital accumulation, and foreign investment increase. Spending on research and development by 1% respectively.

Table 5. long and short run results

Co.	Variable	Long run		Short run	
		coefficients	Prob.	Coefficients	Prob.
South Korea	LOG(PAT)	0.431980	0.0086	0.223170	0.0706
	LOG(FDI)	0.139950	0.0597	0.080295	0.0446
	LOG(RD)	0.198317	0.6758	0.113783	0.6901
	LOG(GFCF)	0.743535	0.1146	0.705064	0.0000
	C	-4.897909	0.0000		
	ECM			-0.573741	0.000
Germany	LOG(PAT)	3.069782	0.0000	0.429744	0.0021
	LOG(GFCF)	1.269403	0.0003	0.522016	0.0043
	LOG(FDI)	-0.119050	0.2521	-0.011910	0.4648
	LOG(RD)	-0.266118	0.7535	-1.170340	0.0045
	c	-35.70253	0.0000		
	ECM			-0.411230	0.000
United States	LOG(PAT)	-0.651520	0.0884	0.441307	0.0312
	LOG(GFCF)	1.283862	0.0232	2.616597	0.0000
	LOG(FDI)	-0.003595	0.9888	0.095309	0.0017
	LOG(RD)	0.188040	0.9114	1.732293	0.0090
	c	-0.883342	0.7237		
	ECM			-0.347707	0.000

The ECM value mirrors the speed at which the system moves from a temporary balance to a state of permanent stability. Both the coefficient and the derived ECM are negative at the 1% significance level. According to the ECM values in South Korea, Germany, and united state models, short-term deviations from the long-term equilibrium path are generally adjusted by an average of 57.37 %, 41.12%, 34.77 % each year respectively. The significantly negative ECM coefficient indicates that any long-term disparities among the model variables will adjust or align with the long-term equilibrium.

This study employed various diagnostic tests to verify the reliability of the ARDL findings. The Breusch-Godfrey Langrage Multiplier (LM) test for autocorrelation is displayed in Table 6. The findings indicate that there is no serial correlation present. The Breusch-Pagan-Godfrey test for heteroskedasticity demonstrated that the data do not show signs of heteroskedasticity. To assess the normality of the series, the Jarque-Bera Normality test was conducted. The statistics from the Jarque-Bera test and the corresponding p-value indicated that the residuals follow a normal distribution.

Table 6. Results of Diagnostic Tests

Diagnostic tests	**Soth Korea**		**Germany**		**United states**		**Decision**
	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	
Jarque-Bera test	0.147	0.929	2.267	0.321	3.77	0.152	Residuals are normally distributed
Breusch-Godfrey Serial Correlation LM Test:	0.740	0.489	1.951	0.158	3.333	0.082	No serial correlation exists
Breusch-Pagan-Godfrey	0.297	0.969	1.356	0.2638	0.801	0.680	No heteroscedasticity exists
Ramsey Reset test	0.015	0.902	1.648	0.214	1.150	0.309	The model is properly specified

Conclusion

Technological progress influences global competition; nations that develop technology and utilize it effectively within their economic activities tend to have stronger economies. When examining the commodity composition of international trade, it becomes evident that the proportion of technology-driven products or production processes in overall world trade is steadily increasing; the rise in high-value-added products and the monopolistic advantages gained from complex technological goods or processes make this trend more appealing than ever. This study analyzed the influence of patent numbers, serving as an indicator of innovation, on exports from the high and medium-high-tech manufacturing sectors in South Korea, Germany, and the United States over annual periods. Additionally, variables such as Research and Development as a percentage of GDP, Gross Fixed Capital Formation, and Foreign Direct Investment inflows as a percentage of GDP were utilized to elucidate high-tech export levels. The stationarity characteristics of the variables were assessed using panel two-unit root tests, and the existence of a long-term relationship among the variables was examined through cointegration tests. Given that the results from the cointegration tests indicate a long-run equilibrium between the pertinent variables, cointegration coefficients were further analyzed using the ARDL Bounds Test.

The result of long run show that the patent has positive impact on South Korea and Germany high technology exports, in addition, in short run the patent has positive impact on South Korea Germany, and united states high technology exports, thus the patent is the main important determinants of high technology exports. Additionally, the error correction coefficient (ECM) was determined to be both negative and significant, indicating that the error correction mechanism is functioning and that short-term imbalances are rectified over the long term.

Based on the above findings, the study recommends that increasing high-tech exports requires increasing patents. Countries that wish to boost their exports should work to promote and encourage innovation by motivating individuals and companies to present patents in the high-tech sector.

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