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Knowledge and Technological Innovations in the Context of Tourists' Spending in OECD Countries

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Abstract
Tourism is one of those segments where the effect of implemented innovations tends to show relatively quickly. The presented study aims to assess the links between knowledge and technological innovation and tourists' spending in a sample of developed countries. To this end, the research relied on annual data (2010-2019) from selected OECD countries (n = 36). Data presenting the innovation potential (Knowledge & technology Global Innovation Index) of selected countries (knowledge creation, impact of knowledge, and knowledge diffusion) was included in the analyzes. Four indicators represented tourism: Business Tourism Spending, Leisure Tourism Spending, Domestic Tourism Spending, Visitor Exports - Foreign spending. The panel regression analysis showed that demonstrable links were proved only for some assumptions, while the identified effects acquired negative trajectories, i.e., in countries where higher tourist spending was identified, lower outputs of innovation activities in the examined areas can be expected. In addition, significant negative links were discovered between the indicators of the creation of knowledge and visitor exports, as well as the dissemination of knowledge and domestic tourism spending. For more accurate results, further analyzes and examinations of interconnections in a different country structure are needed.

Key Words: international tourism, spending, Global Innovation Index, cluster analysis, regression analysis

JEL Classification: C40, H50, M20.

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1. Introduction

In innovation, the speed with which changes are being implemented is increasing. Changes provide a significantly greater number of opportunities in all areas of industry. This also applies to tourism. The current situation leads to innovations thanks to collaboration rather than the individual effort of business entities. Much empirical research points to the presence and importance of innovation in both the technological and knowledge fields and to the extent that selected performance indicators of such an entity have the potential to influence. One of these indicators is clearly the tourists' spending in destinations, which is one of the main drivers of tourism. The tourism industry has been growing steadily for over half a century and is one of the main areas of international trade.

Tourism is currently the fourth largest source of export earnings, with only the oil, chemical, and automotive industries reaching higher numbers (Seghir et al. 2015). This sector directly makes 4.4% of GDP, is responsible for 6.9% of jobs and 21.5% of services in OECD countries on average, and its growth provides real prospects for sustainable and inclusive development. However, integrated and forward-looking policies and innovations (OECD 2020) are needed to ensure that this growth benefits people, cities, and businesses more sustainably. Therefore, it is logical that many new technological and knowledge innovations will be introduced in the tourism segment and will even become a necessity in terms of competitiveness of any entity operating in the tourism sector. Therefore, a deeper examination of the potential relationship between innovation and spending on travel is needed. Therefore, this paper aims to assess the links between knowledge and technology innovation activities and tourists' spending.

2. Literature review

The use of innovative technologies has a significant impact on business indicators (Civelek et al., 2021a), forecasts, order rates, logistics and automation, as well as the ability to control and advertise. Such innovations are important due to the transformation (Civelek et al., 2021b), profitability (Stefko et al., 2020), and competitiveness (Kliuchnikava, 2022; Janovska et al., 2012) that positively affect their performance (Stefko et al., 2019), and competencies of companies to manage their innovation potential (Kolková et al., 2022), production capacity (Kutac et al., 2013), and financial issues (Charaia et al., 2021). Innovations also carry high importance for regions that significantly impact economic development in various areas (Jemala 2021). Today, we do not have enough information on how the business sector creates these innovative social solutions, especially in the field of tourism and its various sub-categories. This slows down the pace of innovation, and Mahato et al. (2021) suggest that the literature on entrepreneurship in tourism should be inspired by design thinking and human-centered innovation.

In the tourism segment, several sectors operate in parallel, thus providing a more integrated experience and supporting the development and relevant innovation (Aquino et al. 2018). This mix of products and services, which is complemented by interactions between communities and organizations active at destination, drives innovation potential on several levels simultaneously through different actors (Pikkemaat et al. 2019). The classical business models, although using tourism-based innovations, still run on capitalist models. However, this leads to less benefits for the host community (Dredge 2017).

A strong competitive environment means that destinations and tourism play a key role in attracting visitors. And undoubtedly, economic growth and innovation in a wide range of areas also contribute to this (Ratten et al. 2019). In essence, these systems have a competitive range of services which attract tourists (Weng et al. 2020). Tourists on a global scale significantly benefit from the implementation of technological and knowledge innovations. Interesting examples can be found in Denmark (Dueholm et al. 2014), Korea (Chung et al. 2018), or in the film industry (Ding et al. 2018), the gaming industry (Jang et al. 2019) or museums (Recupero et al. 2019).

In general, the innovation dissemination model in the tourism segment is also considered to be a process in which innovation is communicated through selected channels to all participating members over a specific period of time (Rogers 1983). The definition formulated in this way proved to be very suitable given the way tourists accept technological innovations (Agag et al. 2016). This model of dissemination of innovations is also used for dissemination of knowledge – on this basis, the relevant members get information about these innovations (Pan and Lin 2011).

Tourists' technological and knowledge readiness differ from one another and thus also their willingness to accept the innovation differ (Chung et al. 2015). This perceived level of innovation readiness among tourists affects the relationships between the innovated services and the perceived satisfaction with them / perceived quality. All this can help in predicting future consumer behavior in the destination (Wang et al. 2017). This aspect was examined by Kim et al. (2020) in their study of the moderating role of innovation readiness. The study by Jemala (2021), in turn, pointed to Asian dominance in matters of technological innovation management in terms of the number of technological patents, as well as growth dynamics and the ability to manage Covid-19 pandemic or other critical situations.

There are two main problems with innovation. The first is the initiation of innovation (Kane et al. 2015). There are still many business segments that have trouble initiating innovation (Correani et al. 2020). Innovation requires the business to identify the need for innovation, adapt to it, apply valuable knowledge from all available sources, and assess the accompanying opportunities that the innovation has brought (Kohli and Melville 2019). However, it is a very challenging task because it is closely related to the customer experience (Lyytinen et al. 2016). Therefore, the ability of companies to adapt the direction of their key activities to the upcoming trajectory determined by the planned innovation is important (Yoo et al. 2012). The second main problem is the implementation itself, which requires the acquisition of the necessary competencies in all organizational units of the company (Morgan 2019). Bridging these imaginary boundaries often causes significant problems for companies (Svanh et al. 2017).

Several studies have also addressed knowledge innovation in the context of tourism, in particular shared knowledge at the level of countries, regions, cities and tourism organizations (Maisonobe et al. 2016; Potter et al. 2020; Yao et al. 2020). Their aim was to examine common shared knowledge networks and their impact on innovation performance at different levels. Such a network of shared knowledge is one of the key factors in the dynamic process of innovation, which has also been shown in several studies (Liu et al. 2020; González Moreno et al. 2019)

3. Methods

Based on the above, the analysis focused on demonstrating the relationships between the global innovation index taking into account knowledge and technology and the tourists' spending in developed countries.

Sample

The research analyzed data of the selected OECD countries from 2010 to 2019 (n=36 – Australia (AUS), Austria (AUT), Belgium (BEL), Canada (CAN), Switzerland (CHE), Chile (CHL), Czech Republic (CZE), Germany (DEU), Denmark (DNK), Estonia (EST), Finland (FIN), France (FRA), United Kingdom (GBR), Greece (GRC), Hungary (HUN), Ireland (IRL), Iceland (ISL), Israel (ISR), Italy (ITA), Japan (JPN), Korea (KOR), Lithuania (LTU), Luxembourg (LUX), Latvia (LVA), Mexico (MEX), Netherlands (NDL), Norway (NOR), New Zealand (NZL), Poland (POL), Portugal (POR), Spain (SPN), Slovakia (SVK), Slovenia (SVN), Sweden (SWE), Turkey (TUR), United States (USA)). The above research objective focused on developed OECD countries, with Colombia being excluded from the sample for being a member of the OECD for only a short period of time. The sample therefore includes 36 Member States OECD.

Variables

Data on tourism spending was obtained from the World Travel & Tourism Council (WTTC, 2020), database, focusing on four indicators:

- Business Tourism Spending (BTS)
- Leisure Tourism Spending (LTS)

- Domestic Tourism Spending (DTS)
- Visitor Exports – Foreign spending (VEFS).

World Travel & Tourism Council describes the variables in question as follows: Business Tourism Spending: spending on business travel within a country by residents and international visitors. Leisure Tourism Spending: spending on leisure travel within a country by residents and international visitors. Domestic Tourism Spending: spending within a country by that country's residents for both business and leisure trips. Multi-use consumer durables are not included since they are not purchased solely for tourism purposes. This is consistent with total domestic tourism expenditure. Visitor Exports (Foreign spending): spending within the country by international tourists for both business and leisure trips, including spending on transport, but excluding international spending on education (WTTC, 2020). The World Travel & Tourism Council database provided gross data in billions (USD 1,000,000,000 per country). In the first step data was categorized by the population of OECD countries (2020). The follow-up calculations quantified the spending per capita of a particular country. In the next step, data was categorized on the basis of the purchasing power parity as follows: OECD.Stat - Purchasing Power Parities (PPP) for GDP per capita Current PPPs (OECD pre-OECD index, OECD average = 100), thus reaching the final form of tourists' spending indicators.

The knowledge and technology innovation variables included data obtained from the annual INSEAD WIPO (2020) reports:

- knowledge creation – KCR
- knowledge impact – KIP
- knowledge diffusion – KDF

All three variables can be characterized as elements of novelty creation and innovation, while INSEAD WIPO (2020) in the Global Innovation Index report describes these in terms of input parameters as follows: KCR (Knowledge creation) - focuses on knowledge creation (number of resident patent applications, patent cooperation, submitted applications for improving models, scientific and technical publications, citation H index); KIP (Knowledge impact) - focuses primarily on the impact of knowledge, especially in micro and macroeconomic perspectives (GDP per employee, new business density, software expenditure, ISO 9001 certification, share of high-tech and medium-high-tech production); KDF (Knowledge diffusion) - focuses on the dissemination of knowledge (income from intellectual property, stimulated net high-tech exports, exports of ICT services, net outflows of foreign direct investment).

Analytical processing

The research made use of analytical methods of descriptive and inductive statistical analysis. With regard to descriptive statistics, Mean, 5% Trimmed Mean, Median, Standard Deviation, Interquartile range (IQR), Skewness, Kurtosis, Minimum, Maximum were used.

The second part of the paper presents the outputs of the panel regression analysis – for that purpose, 3 models were used: 1. Pooling Model, 2. Oneway (individual) effect Within the Model, 3. Oneway (individual) effect Random Effect Model: Swamy-Arora's transformation. Regression coefficients were estimated using robust methods. Pooling model - Heteroskedasticity-Consistent Covariance Matrix Estimation, Within Model - Arellano methods of estimate, Random model - White 2 were used. Emphasis was also placed on procedures capable of selecting the most appropriate method for estimating results such as: Breusch-Pagan Test, Wooldridge's test for unobserved individual effects (Wooldridge, 2010), Baltagi and Li one-sided LM test, F test for the presence of individual effects (or time effect, Hausman Test for Panel Models, Angrist Newey's test (Wooldridge, 2010).

In the final parts of the research, the cluster analysis was employed – Partitioning Around Medoids (PMM) and Manhattan distances (Schubert & Rousseeuw, 2019)). The silhouette method was used to estimate the number of clusters (Kassambara, 2017).

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The programming language R (R Core Team 2020), v. 4.1.0 was used for analytical processing in R Studio - RStudio, Inc., Boston, MA, U.S.

4. Results

The first part of the research focused on the basic statistical description of the indicators used, the second part focused on the panel regression analysis and the last part evaluated the outputs of the countries themselves using cluster analysis.

Table 1. **Descriptive analysis of selected indicators**

Characteristics	BTS	LTS	DTS	VEFS	KCR	KIP	KDF
Mean	522.47	2099.25	1430.18	1191.53	42.06	43.53	39.59
5% Trim Mean	488.55	1964.41	1384.76	1047.80	41.57	43.64	38.72
Median	492.41	1824.11	1368.64	838.12	39.25	43.75	37.10
Std. Deviation	349.25	1297.32	849.94	1117.75	19.56	8.99	16.45
IQR	402.68	1505.28	1347.09	1004.49	31.20	12.10	24.00
Skewness	2.45	2.14	0.63	3.34	0.34	-0.14	0.69
Kurtosis	10.72	7.14	-0.35	15.72	-0.64	0.12	-0.01
Minimum	112.99	454.76	197.53	66.97	3.90	17.70	8.80
Maximum	2599.15	8863.93	3851.90	8322.97	99.70	72.50	90.30

Source: own evaluation

Table 1 summarizes the results of the descriptive analysis, and based on the characteristics of the central trend, it could be concluded that the highest rate of tourists' spending was recorded in the LTS (mean = 2099.25 ± 1297.32). This result was expected, as this area of tourism covers the widest range of activities. The lowest rate of spending was identified for the most specific area which is BTS (mean = 522.47 ± 349.25). Assuming that the theoretical value of innovation activities is in the range of 1-100, the average outputs suggest that there is some room for improvement in this area. All indicators of innovation activities are approximately at the same level, while the lowest level was measured for KDF (mean = 39.59 ± 16.45). From the point of view of position characteristics, more significant deviations were manifested mainly in Kurtosis in the spending indicators. The relatively large differences between countries are emphasized by the comparison of the minimum and maximum values. Table 2 shows details of country comparisons.

Table 2. **Arithmetic average of selected indicators per country**

Krajina	**BTS**	**LTS**	**DTS**	**VEFS**	**KCR**	**KIP**	**KDF**
AUS	547.34(21)	2651.46(27)	2550.98(33)	647.82(12)	36.58(16)	41.9(16)	21.35(3)
AUT	579.98(22)	3503.43(33)	2098.14(29)	1985.27(30)	42.13(21)	39.17(9)	34.83(18)
BEL	429.6(16)	1208.42(8)	752.54(12)	885.48(20)	46.07(22)	40.77(11)	36.67(19)
CAN	662.11(28)	1110.19(6)	1382.25(18)	390.05(4)	46.25(23)	41.15(12)	38.28(21)
CZE	274.56(11)	1178.54(7)	600.24(7)	852.86(19)	40.76(19)	51.63(31)	38.19(20)
DEU	616.66(27)	2944.88(31)	3067.31(35)	494.24(8)	66.58(32)	43.98(21)	45.95(24)
DNK	949.99(34)	1504.86(15)	1381.31(17)	1073.55(25)	53.32(26)	44.61(23)	41.79(22)
EST	667.23(29)	2123.44(23)	718.95(11)	2071.71(31)	32.59(13)	52.29(32)	33.93(17)
FIN	787.44(31)	2050.94(22)	2082.33(28)	756.05(16)	61.55(30)	42.62(18)	58.82(31)

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FRA	494.49(18)	2049.79(21)	1703.98(24)	840.3(18)	38.81(17)	41.78(15)	47.41(26)
GBR	909.18(33)	1905.99(20)	2319.83(30)	495.34(9)	59.1(29)	54.55(34)	45.2(23)
GRC	231.9(7)	3356.29(32)	1405.75(20)	2182.45(32)	19.59(5)	34.58(3)	20.23(2)
HUN	136.5(1)	1220.84(9)	391.91(2)	965.42(22)	23.24(7)	49.39(29)	51.31(28)
CHE	517.46(19)	2884.63(29)	1938.44(26)	1463.64(26)	83.61(36)	55.27(36)	65.1(35)
CHL	268.64(9)	1444.86(14)	1393.81(19)	319.69(2)	13.61(2)	37.14(7)	24.17(6)
IRL	610.72(25)	1354.3(12)	445.54(3)	1519.49(27)	32.14(11)	55.04(35)	79.57(36)
ISL	1833.72(36)	7018.31(36)	2941.74(34)	5910.28(36)	48.08(24)	41.23(13)	31.37(15)
ISR	330.36(12)	1637.96(16)	951.53(15)	1016.79(23)	58.76(28)	43.78(20)	60.22(32)
ITA	610.95(26)	2487.39(25)	2358.97(31)	739.37(15)	34.48(15)	49.56(30)	31.12(14)
JPN	598.45(24)	1228.51(10)	1616.64(22)	210.31(1)	57.3(27)	35.31(4)	52.19(29)
KOR	180.41(5)	721.94(2)	491.1(6)	411.25(5)	73.86(34)	39.72(10)	46.65(25)
LTU	251.93(8)	900.14(5)	489.91(5)	662.17(13)	18.51(3)	38.3(8)	22.2(4)
LUX	186.15(6)	3725.33(34)	697.66(10)	3213.83(35)	41.51(20)	35.38(5)	54.73(30)
LVA	273.65(10)	1359.09(13)	689.5(9)	943.24(21)	18.57(4)	44.08(22)	28.48(11)
MEX	156.94(3)	2553.49(26)	2390.34(32)	320.09(3)	9.30(1)	30.33(1)	30.36(12)
NDL	435.95(17)	1254.94(11)	880.26(13)	810.64(17)	62.51(31)	45.56(25)	61.54(33)
NOR	583.46(23)	1817.94(18)	1689.36(23)	712.04(14)	39.74(18)	41.59(14)	30.76(13)
NZL	1065.99(35)	4683.47(35)	3556.52(36)	2192.94(33)	52.42(25)	41.9(17)	22.58(5)
POL	179.68(4)	484.2(1)	213.45(1)	450.43(7)	24.64(9)	35.75(6)	27.38(9)
POR	533.56(20)	2890.42(30)	1205.31(16)	2218.67(34)	24.30(8)	43.54(19)	25.18(7)
SPN	372.28(14)	2798.03(28)	1414.81(21)	1755.51(29)	32.58(12)	47.15(27)	33.81(16)
SVK	367.06(13)	887.14(4)	636.98(8)	617.23(11)	22.24(6)	46.77(26)	27.38(10)
SVN	394.69(15)	2235.95(24)	907.75(14)	1722.89(28)	32.76(14)	45.37(24)	26.01(8)
SWE	906.23(32)	1888.79(19)	1730.99(25)	1064.03(24)	74.54(35)	47.47(28)	62.28(34)
TUR	138.51(2)	853.28(3)	451.38(4)	540.41(10)	25.4(10)	33.96(2)	18.82(1)
USA	725.06(30)	1653.84(17)	1939.12(27)	439.78(6)	66.63(33)	54.27(33)	49.38(27)

Source: own evaluation

Table 2 presents the average outputs of the selected indicators, while the average was formed by the values for the selected years. In the table, in addition to the average value, the order identifiers also appear. Identifier 1 represents the lowest value and identifier 36 the highest value among countries. Taking a more closer look at the outputs in question, it was possible to observe that higher outputs are associated with countries with a better developed economies.

Table 3. **Regression models conditions**

Model	**BPT**	**WT**	**BLT**	**F_Geo**	**F_Year**	**HT**	**RHT**	**ANT**
KCR–>BTS	**36,6†**	**3,38†**	**13,48†**	**161,87†**	1,02	**19,04†**	**9,48*****	75,50
KCR–>LTS	0,22	**3,78†**	**5,90†**	**90,44†**	0,68	0,77	0,82	74,38
KCR–>DTS	0,90	**3,68†**	**14,40†**	**445,72†**	0,44	**9,34*****	**4,50****	63,15
KCR–>EFS	**6,81*****	**3,95†**	**3,24†**	**68,51†**	0,78	0,09	0,10	71,32
KIP–>BTS	2,52	**3,55**	**13,33**	**200,64**	0,94	**6,53****	**5,99****	56,22

		†	†	†				
KIP–>LTS	**19,25†**	**3,77†**	**5,93†**	**90,44†**	0,63	0,19	0,27	101,25
KIP–>DTS	1,59	**3,75†**	**14,56†**	**492,61†**	0,21	<0,001	<0,001	42,47
KIP–>EFS	**12,32†**	**3,85†**	**3,61†**	**67,66†**	0,87	0,30	0,31	108,37*
KDF–>BTS	3,39*	**3,62†**	**13,13†**	**210,84†**	0,54	2,22	2,56	75,61
KDF–>LTS	**18,02†**	**3,76†**	**6,15†**	**89,70†**	0,60	0,73	0,73	**134,31*** **
KDF–>DTS	**13,86†**	**3,83†**	**14,22†**	**498,70†**	0,18	0,06	0,08	75,37
KDF–>EFS	**10,59*** **	**3,94†**	**3,81†**	**68,22†**	0,80	0,14	0,14	**134,66*** **

*Note: * p value < 0,1; ** p value < 0,05; *** p value < 0,01; † p value < 0,001.*
Note II: Breusch–Pagan test – BPT; Wooldridge's test for unobserved individual effects – WT; Baltagi and Li one-sided LM test; F test for the presence of individual effects – F_Geo, F_Year; Hausman Test for Panel Models – HT, Angrist Newey's test – ANT
Source: own evaluation

Table 3 presents the evaluation of selected conditions for the application of regression models. The results support the methods selected for estimating regression coefficients. The residue variability (BPT) constancy test indicates that in most cases there is a presence of significant heteroskedasticity at an α level of less than 0.05. The serial correlation was assessed by the Wooldridge's Unobserved Effects Test and the Baltagi-Li one-sided LM test, and in all cases a significant output at an α level below 0.05 was identified. Thus, the use of robust estimation methods was justified. The F test acquires significant values (p <0.05) of the coefficients in all cases in the country test, but in zero case in terms of years dimension. In view of the above, it seems appropriate to take into account the effects countries have. Preference of the model with fixed/ random effects is supported by the tests listed in the last three columns of the table. If the Hausman test and its robust version show significant results, the fixed effects model seems more appropriate, otherwise random model should be used. Angrist and Newey's test of the within model with a p value lower than 0.05 highlights the significant limitations of the model with fixed effects. Based on the above, this model is preferred in six cases: KCR–>BTS; KCR–>DTS, KIP–>BTS.

Table 4. **Output of regression models**

Model	Coef	Pooling (SE)^{vcov}	Within (SE)^{arellano}	Random (SE)^{white}
KCR–>BTS	β	6,66† (1,90)	0,24 (0,64)	0,66 (0,54)
	α	221,71*** (70,32)		473,92† (44,26)
KCR–>LTS	β	3,64 (6,88)	-3,53 (3,54)	-2,75 (2,58)
	α	1824,74† (332,09)		2 093,52† (194,44)
KCR–>DTS	β	13,55** (6,33)	-3,28 (2,00)	-0,92 (1,10)
	α	860,49*** (287,74)		1 468,79† (143,64)
KCR–>VEFS	β	-2,65 (4,61)	-4,33* (2,35)	**-4,10** (2,00)**
	α	1139,00† (239,50)		1 199,83† (133,73)
KIP–>BTS	β	7,61** (12,32)	0,46 (0,52)	0,54 (3,09)
	α	171,68 (617,81)		478,38† (212,32)
KIP–>LTS	β	-4,62 (11,36)	1,66 (4,84)	1,52 (1,18)

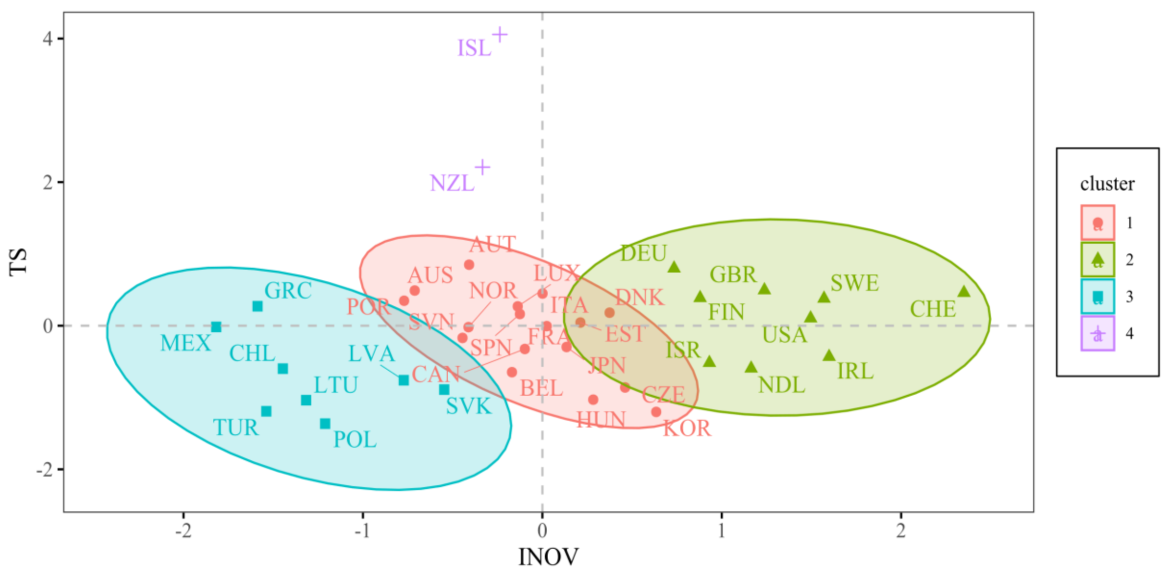
	α	2,177,95† (527,04)		1 912,04† (152,25)
KIP–>DTS	β	-0,16 (8,84)	0,17 (2,21)	0,17 (2,34)
	α	1 437,23*** (425,33)		1 422,96† (149,61)
KIP–>VEFS	β	5,02 (8,84)	0,02 (3,52)	0,17 (2,34)
	α	809,99* (425,33)		1 020,12† (149,61)
KDF–>BTS	β	2,62 (2,21)	-0,91** (0,42)	-0,81* (0,42)
	α	398,00† (103,63)		533,63† (47,43)
KDF–>LTS	β	-5,91 (8,33)	1,87 (4,42)	1,40 (2,57)
	α	2 211,39† (407,34)		1 922,64† (196,73)
KDF–>DTS	β	-4,55 (7,73)	-2,40 (1,13)	**-2,42*** (0,83)**
	α	1 609,63† (371,44)		1 525,82† (148,05)
KDF–>VEFS	β	-0,54 (5,58)	1,78 (3,47)	1,60 (2,00)
	α	1 048,65† (263,31)		964,15† (137,85)

*Note: vcov: Robust Estimation; arellano: Arellano estimator; white: White 2 estimator; * p value < 0,1; ** p value < 0,05; *** p value < 0,01; † p value < 0,001.*

Source: own evaluation

Table 4 shows that when examining the above, only two models can be considered significant, of which a random estimate of coefficients was preferred (β: KCR–> EFS = -4.10 **; KDF–> DTS = -2.42 ***). The β coefficients acquire negative values. This output can be freely interpreted as meaning that countries with a lower level of creative material production (KCR) show a higher rate of foreign visitors spending, while countries with a lower level of intellectual property representation (KDF) show a higher rate of domestic visitors spending. This can be transformed into a general connection that with the growth of the above-mentioned dimensions of knowledge and technology, a certain decrease in the areas of spending in question can be expected.

Figure 1. **Cluster map - knowledge, technologies and spending**



Source: own evaluation

Figure 1 presents four clusters, where the third cluster groups countries with lower spending and also with lower outputs of knowledge and technology innovation. In this case, Slovakia is part of a cluster that can be perceived with more negative intentions. Sweden, Switzerland, as well as the United Kingdom, are among the countries with the most positive results.

5. Discussion and Conclusion

The results presented in the outputs, in particular those which appear to be significant, point to the fact that the more developed the countries in terms of creativity and related outputs of a different nature, the lower the tourists' spending can be expected. The significance of the outputs was random rather than systematic. The results support the all-around benefits of innovation, creativity, and scientific and technological outputs, although these outputs do not directly translate into a significant increase in tourists' spending. Del Chiappa and Baggio's (2015) results confirm the validity of this statement in their study on smart tourism, as they specifically mention the important role of knowledge in building an effective tourism system. The present times brought along the phenomenon of the sharing economy, which is, to a large extent, the result of creative processes (for example, shared rides, accommodation with someone in the household, etc.), while the effects of these trends on tourism as a whole are indisputable (Dredge and Gyimóthy 2015). It is these specifics that have the potential to impact spending in selected areas negatively. In this respect, the problem of the shared economy lies in the fact that not all tourists' expenses are properly recorded. In a sense, the results also show that businesses operating in tourism (especially small businesses) are not able to utilize the outputs of creative (knowledge) activities as well as new technologies (Alford and Jones, 2020).

From the point of view of e-commerce, these results do not directly point to a clear increase in expenses and the associated increase in sales caused by innovation. This area should also be explored in further research. However, the hereunder innovations also have a different dimension - they streamline the e-commerce workflow of business entities and thus indirectly affect their economic indicators. In addition to the undeniable benefits of the research, the paper has several limitations. The research has been carried out in highly-developed countries. It would be a mistake to generalize the results to less developed countries. Future research shall, therefore, focus on comparing outputs with an emphasis placed on the differences between developed and emerging economies.

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