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Knowledge Space, Relatedness and Complexity: A Regional Analysis in Turkey

Bilgi Alanı, İlişkililik ve Karmaşıklık: Türkiye İçin Bölgesel Bir Analiz

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ABSTRACT

Regional development policies based on regions' core strengths are key for innovation. For sustainable growth, regions would discover their own growth paths grounded on their core knowledge base. Although there are studies focusing on regional clustering of economic activity in Turkey, little is known related to regions' potential to attract new technologies based on their core strenghts. The first objective of the paper is to map *knowledge space* in Turkey for 2010 and 2017. The second objective of the paper is to understand *relatedness and knowledge complexity* in Turkey's NUTS3 regions. The third objective is to demonstrate the relationship of *regional innovativeness* with *relatedness and knowledge complexity* across Turkey's regions. *Relatedness* of the regions is operationalized by relatedness density. *Knowledge complexity* is operationalized by knowledge complexity index. We use regression analysis to understand the correlation of patent applications with regions' relatedness density and knowledge complexity. As a control variable, diversity variable is used. The analysis demonstrates that knowledge space in Turkey became denser between 2010 and 2017 and there are variations across regions with respect to relatedness and knowledge complexity. Diversity and relatedness density are positively correlated with patent applications while complexity does not have a correlation with regional innovativeness.

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ÖZ

Bölgelerin güçlü yönlerine dayalı bölgesel kalkınma politikaları, yenilikçilik için anahtar niteliğindedir. Sürdürülebilir büyüme için her bölge kendi öz bilgi havuzu üzerinde temellendirilmiş büyüme yollarını keşfetmelidir. Türkiye'deki ekonomik faaliyetin bölgesel kümelenmesi konusuna odaklanan çalışmalar bulunmasına rağmen, bölgelerin güçlü yönlerine dayalı yeni teknolojileri çekme potansiyelleri konusunda kısıtlı bilgi bulunmaktadır. Bu makalenin ilk hedefi, Türkiye'nin 2010 ve 2017 yıllarına ait *bilgi alanının* haritasını çizmektir. Makalenin ikinci hedefi, Türkiye'deki NUTS3 bölgelerinin 2010 ve 2017 yıllarındaki *ilişkiliik ve bilgi karmaşıklığını* anlamaktır. Üçüncü hedef, Türkiye'deki bölgelerin *bölgesel yenilikçiliği (patent başvuruları)* ile *ilişkililik ve bilgi karmaşıklığı* arasındaki ilişkiyi göstermektir. Bölgelerin *ilişkililikleri*, ilişkililik yoğunluğu değişkeni ile ölçülmektedir. *Bilgi karmaşıklığı* ise bilgi karmaşıklığı endeksi ile ölçülmüştür. Patent başvurularının bölgelerin ilişkililik yoğunluğu ve bilgi karmaşıklığı ile korelasyonunu anlamak için regresyon analizi kullanılmıştır. Kontrol değişkeni olarak, *çeşitlenme* değişkeni kullanılmıştır. Analizler, Türkiye'deki bilgi alanının 2010 ve 2017 arasında daha yoğun bir hale geldiğini ve ilişkililik ve bilgi karmaşıklığı bakımından bölgeler arasında farklılıklar olduğunu göstermektedir. Çeşitlenme ve ilişkililik yoğunluğu patent başvuruları ile pozitif yönde bir korelasyona sahipken, karmaşıklığın bölgesel yenilikçilikle ilişkili olmadığı görülmüştür.

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1. INTRODUCTION

Unlike the "one size fits all" approach to regional development, it is well known that enabling each region to have a distinct focus on its unique characteristics is key to sustainable competitive advantage (European Commission, 2020a). In 2011, Smart Specialisation Strategy was identified as the main programme by the European Union for reaching its smart, sustainable, and inclusive growth objectives. It has also been described as a supporting tool for its Territorial Cohesion Policy which is essential for eliminating differences between regions by ensuring a balanced development. It is defined as an innovative perspective based on integrated and place-based economic transformation by focusing on each region's strengths, competitive advantages, and potential for excellence (Foray et al., 2012). The role of conducting place-based innovation strategies also comes to the forefront in creating clusters for high-value added and innovative investments that require high amount of cumulative knowledge (Widuto, 2019). Smart innovation strategies make it possible to create interregional clusters by linking regions with similar knowledge and enable the accumulation of knowledge required for progress. Therefore, the focus on regional specialization policies should be on region's competencies where each region discovers its own growth path.

Potential economic activities of a region should be determined by taking into account the relatedness of the industries in the region (the extent to which a new technology/occupation/industry is related to pre-existing skills and capabilities in the region) and technological complexity of the industries (potential socio-economic impact of diversifying into specific activities) (Hidalgo and Hausmann, 2009; Hidalgo et al., 2018; Balland et al., 2019). This concept is fundamental in smart specialization policies. Balland et al., (2019) propose that regions should develop on sectors that are technologically related to the regions' core strengths and are difficult to replicate outside the region. Relatedness and complexity are two key dimensions in choosing sectors for regional smart specialization.

In Turkey, early studies with a distinct focus on regional specialization are on cluster formation in Turkey (see, Çelik et al., 2019 for a review). The studies demonstrate geographical distribution of economic activity. There are also studies with special focus on technological composition of clusters. Kaygalak (2013) propose that none of the identified clusters include high-tech sectors. Kaygalak and Reid (2016) and Gezici et al., (2017) further demonstrate that increases in sectoral agglomerations tend to be within the medium-low and medium-high technology sectors. In general, existing studies confirm that Turkey's industrial activities contain medium and low technologies.

In relation to the diversity of economic activities and knowledge bases and, indicators of regions' core strengths, Kuştepeli et al., (2013) explore the impact of related variety on economic performance of the regions. Following the regional innovation policy model, based on the idea of constructing regional advantage (Asheim et al., 2011), Gülcan et al., (2011) demonstrate differentiated knowledge bases in Turkish textile industry.

Although existing studies in Turkey reveal evidence on differences in spatial distribution, technology composition and knowledge of economic activities, little is known on how different technology classes are connected to each other as well as how relatedness and knowledge complexity of the regions have impact on regional innovativeness. Relatedness shows potential for regions' branching opportunities into new and related technologies. Related technologies could be source of creating and developing innovations. Similarly, complexity of knowledge indicates that regional capabilities are unique and hard to imitate in other regions, thus creating source of regional competitiveness.

Building upon the smart and inclusive growth priorities defined by the EU, the paper focuses on the role of knowledge for strengthening innovation in individual regions. Knowledge-based economy dimension of the Smart Specialization framework can be regarded as an approach that will help regions to identify and develop their own competitive advantages, and as a result boost growth and jobs across regions (European Commission, 2020b). Thus, this paper aims to contribute designing policies for regional development based on regions' local competitive assets and own competitive advantages by tracing undiscovered opportunities within regions.

There are three aims of the paper: The first aim is to map *relatedness between technology classes* in Turkey for 2010 and 2017. The second aim is to understand relatedness (*branching opportunities*) and *knowledge complexity* in Turkey's regions for 2010 and 2017. The third aim is to demonstrate *how relatedness and knowledge complexity are related to regions' innovativeness.*

The paper proceeds as follows. In section 2, theoretical background of the regional diversification and economic complexity concepts is explained. In section 3, the data and analysis methods used in the study are presented. In section 4, findings on knowledge space, and relatedness and complexity estimations as well as the econometric analysis are shown. In section 5, a conclusion based on our findings is provided.

2. THEORETICAL BACKGROUND

The theory is based on the view that regional competitive advantage depends on the conditions on the use of regions' core knowledge and competencies. This idea has grounds on the stream of literature on regional innovation systems (Freeman, 1995; Cooke et al., 1997) and learning regions (Morgan, 1997; Lundvall and Johnson, 1994). The work on constructing regional advantage brings together the concepts like related variety, knowledge bases and policy platforms (Asheim et al., 2011). As suggested by Balland and Rigby (2017), geography has a significant role in determining the emergence and evolution of knowledge.

The literature on regional accumulation of economic activities starts with the work of Marshall (1890) on agglomeration externalities. The central idea is that economic performance of regions is related to regional specialization and co-location of economic activities. Jacobs (1969) further proposed that different industries where there is variety of economic activities causes diversification externalities. Jacobian externalities cause knowledge spillovers between different industries and diversification leads to more innovative regions. The evolutionary discourse (Nelson and Winter, 1982; Frenken et al., 2007; Boschma and Frenken, 2006) focuses on evolutionary principles to explore how firms, industries, regions change over time. Regional growth is a dynamic process and path dependent (Kogler et al., 2013; Martin and Sunley, 2015). Central to sustainable long run growth is the influence of the capacity to produce economically valuable knowledge and innovativeness (Schumpeter, 1939; Nelson and Winter, 1982). However, it is also well documented and argued that distribution of knowledge is uneven across geographies thus causing differences in economic growth and development (Whittle and Kogler, 2019). Production of knowledge and innovativeness explain differences in economic performance of the regions (Schumpeter, 1942; Solow, 1956; Nelson and Winter, 1982; Romer, 1990).

In their work on smart specialization, Balland et al., (2019) combine regional diversification literature (Hidalgo et.al., 2018; Neffke et al., 2011) and economic complexity literature (Hidalgo and Hausmann, 2009) and argue that relatedness and knowledge complexity are key concepts for a place-based policy (Boschma, 2014). Relatedness concept is related to the idea that knowledge creation is the combination of existing ideas. Foundations of knowledge and innovation are related to re-construction of the components of core ideas and therefore an evolutionary process. Frenken and Boschma (2007) propose that diversification of the economic activities is a branching process and the emergence of new technologies is not random and rather dependent on past knowledge. Innovations and new technologies are based on existing set of capabilities (Boschma, 2017).

In addition to the significance of relatedness (as operationalized by relatedness density) for branching opportunities, regions tend to have competitive advantage when the technologies are unique and hard to copy. What is highly valuable for sustainable regional growth is the ability to create knowledge that tends to be complex. Knowledge complexity resulting from valuable and tacit knowledge is difficult to imitate and access by others (Hidalgo and Hausmann, 2009). Balland and Rigby (2017) demonstrate that complexity correlates with the long run patterns of economic performance and regions develop based on their existing knowledge cores.

Following the regional diversification literature and economic complexity literature summarized above the paper aims to test the hypothesis that regional innovativeness is positively correlated with regions' relatedness density and knowledge complexity. Relatedness proposes a relationship between specialization of a new activity and the presence of related activities in that location (Hidalgo et al., 2018). Similarly, complexity as measured by the presence of complex (hard to imitate) activities in the regions results with valuable economic outcomes coupled with tacit knowledge (Rigby et al., 2019; Maskell & Malmberg, 1999).

3. METHODS

3.1. Data

To identify technological fields and compute measures of relatedness and knowledge complexity, we use OECD-REGPAT database January 2020 Edition (OECD, 2020). OECD-REGPAT contains patent data that are linked to the regions utilizing the addresses of the applicants and inventors. Regional patent data covers more than 5500 regions across OECD countries[1]. In this study, we use patent data for the years 2010 and 2017[2]. The patent data is aggregated at NUTS3 level. The data is cleaned and grouped according to World Intellectual Property Organization (WIPO) technology classification "New concept of technology classification, update: May 2008" (Schmoch, 2008). According to May 2008 classification, IPC codes are grouped according to 5 technology classes and 35 sub-technology classes. We use the latest version (July 2019) of WIPO IPC-Technology Concordance Table to group IPC codes of the patents into WIPO technology classes.

3.2. Analysis Methods

3.2.1. Measuring Relatedness

Relatedness is measured by the method following Boschma et al., (2015) and Rigby (2015). The method is based on counting the number of patent claims for a given period that contains a co-class pair of technologies i and j and standardizing this count by the total number of patents that contain i and j. Relatedness between technology i and j (φ_{ij}) is a standardized measure of the frequency with which two IPC classes appear on the same patent. This paper follows the method outlined in Balland et al., (2019). The analysis is completed with EconGeo R package (Balland, 2017). Using relevant directions outlined in EconGeo R, we develop the *knowledge space*, which is a formal demonstration of relatedness between technologies.

Relatedness across space is demonstrated by the knowledge structure of Turkey's NUTS3 regions. Following the method demonstrated in Balland et al., (2019) and use of EconGeo R package, we calculate the density of technology production in the vicinity of individual technologies i for each NUTS3 region (r) in Turkey for 2010 and 2017. Relatedness of the regions is operationalized by relatedness density.

As specified in Balland et al., (2019), the relatedness density of industry i, in region r at time t is presented below:

$$RD_{i,r,t} = \frac{\sum_{j \in r, j \neq i} \varphi_{ij}}{\sum_{j \neq i} \varphi_{ij}} * 100 \quad (1)$$

RDi,r,t is the relatedness density of technology i to all other technologies j where the region r has relative technological advantage (RTA) at time t. It is estimated by using the Equation (1). φ_{ij} is technological relatedness of technology i with technology j. RTA is a binary variable that takes the value 1 when the region has higher share of patents in technology i in comparison to the share of patents in technology i in the country; and 0 otherwise (similar to the notion of location quotient). Relatedness density is therefore the technological relatedness of technology i to all other technologies j in which the region has relative technological advantage (RTA), divided by the sum of the technological relatedness of technology i to all other technologies in Turkey at time t.

We use *average relatedness density* variable to measure regions' potential for branching into new and related technologies. Average relatedness density of regions represents technological flexibility (the structure of the knowledge base) of the regions as demonstrated in Balland et al., (2015) with calculation procedures outlined in EconGeo Package (Balland, 2017). Average relatedness density (technological flexibility) represents the average relatedness of the technologies present in the region to all technological classes that are not yet in the city. Using average relatedness density variable, it is possible to reveal the branching opportunities and potential to diversify into new and related technologies in Turkey's NUTS3 regions.

3.2.2. Measuring Complexity

Quality of the knowledge created in the region is measured by complexity. Knowledge is valuable if it is difficult to replicate outside the geography. Knowledge that is tacit and sticky in the field is a source for competitive advantage in regions.

This paper follows the method proposed by Hidalgo and Hausmann (2009) using export data. Balland et al., (2019) demonstrates the use of the method with patent data. The method connects the regions to technologies in which they have RTA. The complexity is determined by the range and ubiquity of the technologies that the regions use. The variable that measures complexity of knowledge in regions is knowledge complexity index (KCI).

KCI has two components. Diversity is the number of technology classes in which the region (r) has relative technological advantage. Ubiquity is the number of regions that exhibit revealed technological advantage in a given technology (Balland and Rigby, 2017). Diversity and ubiquity are estimated with Equation (2) and Equation (3), respectively.

$$\text{Diversity} = K_{r,0} = \sum_i M_{r,i} \quad (2)$$

Where $M_{r,i}$ is a binary variable that represents whether the region r has RTA in the production of technology i.

$$\text{Ubiquity} = K_{i,0} = \sum_r M_{r,i} \quad (3)$$

Where $M_{r,i}$ is a binary variable that represents the number of regions with RTA in the production of technology i.

[1] The database was produced by counting patent applications rather than an approval-based approach. Since it takes long time (generally two to ten years) for patents to be approved in some cases, it is possible that approval-based counts do not reflect the conjuncture at the relevant period. Therefore, the data consist of application-based patent counts, in line with the more common approach (Maraut et al., 2008).

[2] 2017 was the latest complete data available for Turkey in the REGPAT database during the time of data download.

The KCI combines the information obtained from the diversity and ubiquity variables following the iterations outlined in Hidalgo and Hausmann (2009). The method includes sequentially combining the diversity of regions and ubiquity of technological classes and simultaneously computes Equation (4) and Equation (5) over a series of n iterations:

$$\text{KCI(regions)} = K_{r,n} = \frac{1}{K_{r,0}} \sum_i M_{r,i} K_{i,n-1} \quad (4)$$

$$\text{KCI (technologies)} = K_{i,n} = \frac{1}{K_{i,0}} \sum_i M_{r,i} K_{r,n-1} \quad (5)$$

3.2.3. Exploring Correlation of Relatedness Density and Complexity on Regional Innovativeness

We use regression analysis to find the correlation of relatedness density and complexity with regions' innovativeness. Innovativeness variable measures the number or patent applications in a region at time t (PAT). The independent variables in the model are, average relatedness density (ARD) and regions' knowledge complexity index (KCI) for 2010 and 2017. In order to control for the impact of diversification of industries on patent applications, diversity variable (DIV) (measure of the number of technology classes in which the region has competitive advantage) is added. Data for the two time periods (2010 and 2017) is analyzed.

4. FINDINGS

4.1. Turkey's Knowledge Space (2010 and 2017)

Figure 1 demonstrates relatedness between technology fields in Turkey for the years 2010 and 2017. The size of the circles shows number of patents in each field and the colors indicate broad technology classes as demonstrated in Schmoch (2008). Comparison of two knowledge spaces demonstrates denser network ties among technologies in 2017 in contrast to 2010. Although chemistry has more patent applications in 2010, there is a visible decline in the number of patent applications in the chemistry field in 2017. In 2017, we see higher number of patent applications in electrical engineering where there are also stronger network ties across electrical engineering field with other technology fields, such as mechanical engineering, instruments and other fields.

4.2. Relatedness and Complexity (2010 and 2017)

Geographical distribution of relatedness density demonstrates region's potential for branching. The upper portion of Figure 2 shows regional branching opportunities in Turkey for 2010 and 2017. The map shows that average relatedness density is higher for the western regions. Limited number of years for observations (2010 and 2017 only) does not allow us to capture patent applications in eastern parts of the country, since there are no patent applications in some regions during the two years. However, a rough interpretation of the two maps tells that western regions and Ankara demonstrate higher branching opportunities when compared to other regions.

Knowledge complexity (lower portion of Figure 2) as a measure of uniqueness of technologies for the regions shows that 2010 demonstrates high knowledge complexity index for most of the regions. The idea of complexity is that more complex regions produce more exclusive and

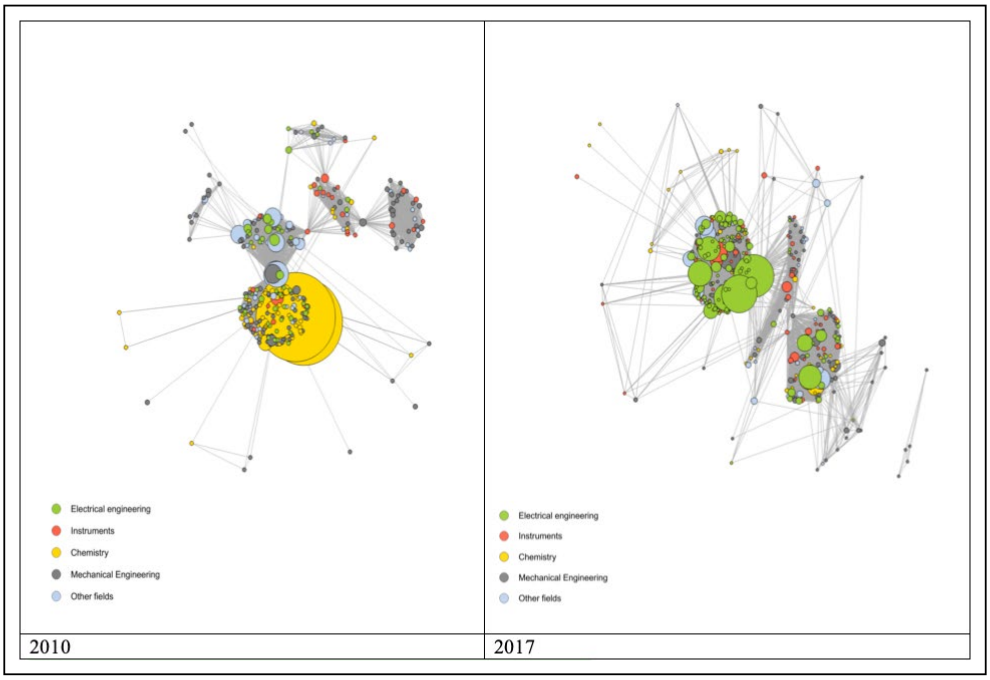

Figure 1. Knowledge Space (2010 and 2017).

Source: OECD REGPAT database (OECD, 2020), own calculation.

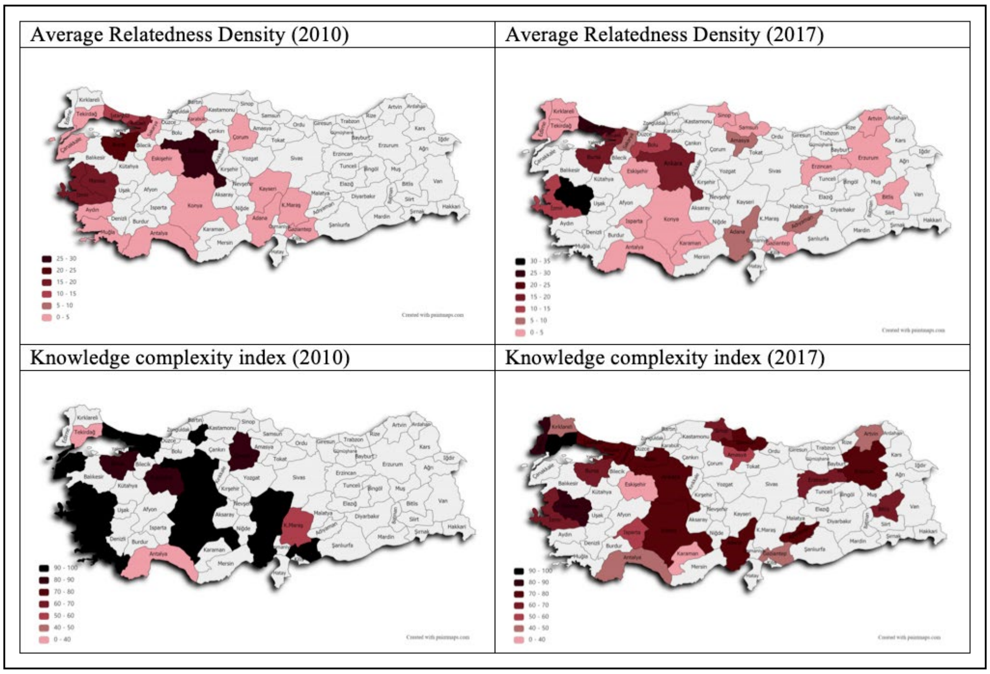

Figure 2. Average Relatedness Density and Technological Complexity Index (2010 and 2017).
Source: OECD REGPAT database (OECD, 2020), own calculation.

non-ubiquous commodities that are produced in relatively few regions (Balland and Rigby, 2017). In 2017, the value of the knowledge complexity index shows more variation across regions, in comparison to 2010. In 2017, it is possible to see complex technologies in the eastern parts of the country as well. More complex technologies are still in the western regions while southern Anatolia has the least complex technologies.

Table 1 shows knowledge complexity index of the technologies in Turkey for 2017. The table shows that the most complex technologies are related to chemistry followed by electrical engineering. The least complex ones are related to mechanical engineering and food chemistry. The classification is according to WIPO classification as proposed by Schmoch (2008)

4.3. Relatedness, Diversity, Complexity and Regional Innovations

While Table 2 presents the summary statistics, Table 3 and Figure 3 show bivariate correlations of the variables. There is a positive and significant correlation between average relatedness density (ARD) and regional diversity (DIV); patent applications (PAT) and regional diversity in 2010. For 2017, the correlation coefficients between ARD and PAT, KDI, DIV are positive and significant. There is a positive correlation between PAT and KCI, as well as low but significant correlation between KCI and DIV.

Regression analysis allows us to perform multivariate analysis to see how average relatedness density and knowledge complexity index correlate with innovativeness. In order to see whether multicollinearity will be a problem in regression estimation, we perform a multicollinearity test using variance inflation factor (VIF). Table 4 presents the results of the VIF values of the independent variables both in linear forms and logarithmic forms

The ARD and DIV variables are highly correlated (see, Table 2 above), and both variables have almost the same VIF value (Table 4). In general, the VIF values are moderately high but they are all smaller than 10. The smallest possible value for VIF is 1 where the value of 1 indicates an absence of collinearity. As a rule of thumb, a VIF value that exceeds 5 or 10 indicates a problematic amount of collinearity (James et al., 2017). All VIF values of the dependent variables are smaller than 10.

Initially we run a linear model with PAT as dependent variable and ARD, DIV and KCI as independent variables, under the assumption of no multicollinearity (VIF value less than 10). Diagnostic tests reveal presence of heteroskedasticity and autocorrelation in the linear model. The linear model is estimated using clustered standard errors to obtain robust estimates in the presence of heteroscedasticity and serial correlation. The model is also estimated using log-linear model with logarithmic transformation of the variables. The log-linear model revealed no presence of serial correlation but the model has heteroskedasticity.

Additionally, in order to compare the pooled OLS with panel model, the model is estimated by using fixed effects and random effects. The results of F-test show that individual effects are insignificant. We also test for individual year effects and conclude that year effects are also insignificant. Even though availability of region and year fixed effects is

Table 1. Knowledge Complexity of Technological Fields 2017

Technological sub field (2 digit)	Technological field (1 digit)	Knowledge Complexity Index
Surface technology, coating	Chemistry	100
Audio-visual technology	Electrical engineering	87.62908518
Telecommunications	Electrical engineering	87.62908518
Digital communication	Electrical engineering	87.62908518
Basic communication processes	Electrical engineering	87.62908518
IT methods for management	Electrical engineering	87.62908518
Machine tools	Mechanical engineering	87.62908518
Pharmaceuticals	Chemistry	84.6247748
Control	Instruments	84.09547457
Micro-structure and nano-technology	Chemistry	84.09547457
Optics	Instruments	83.94625479
Furniture, games	Other fields	82.81812452
Semiconductors	Electrical engineering	82.39059832
Macromolecular chemistry, polymers	Chemistry	80.56186397
Basic materials chemistry	Chemistry	80.41264419
Chemical engineering	Chemistry	79.37985846
Electrical machinery, apparatus, energy	Electrical engineering	78.82646201
Computer technology	Electrical engineering	78.10775104
Handling	Mechanical engineering	77.71417383
Other special machines	Mechanical engineering	77.34334124
Mechanical elements	Mechanical engineering	75.73063929
Materials, metallurgy	Chemistry	74.57414043
Transport	Mechanical engineering	74.16325195
Civil engineering	Other fields	73.86095896
Measurement	Instruments	73.4263042
Environmental technology	Chemistry	71.13063173
Other consumer goods	Other fields	69.89602711
Medical technology	Instruments	69.54993856
Biotechnology	Chemistry	68.50921095
Analysis of biological materials	Instruments	67.19850056
Engines, pumps, turbines	Mechanical engineering	66.76296864
Thermal processes and apparatus	Mechanical engineering	58.61050825
Textile and paper machines	Mechanical engineering	41.94576646
Food chemistry	Chemistry	0

Table 2. Summary Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
PAT	46	42.93478	143.7203	1	780
ARD	46	8.26087	8.365099	0	31
KCI	46	72.2462	24.2324	0	100
DIV	46	3.543478	3.874168	1	17

Since there are no patent applications in some regions during the two years, we get 46 observations in total. In 2010, 20 regions applied for patents while this number was 26 in 2017.

rejected, results of the fixed effects model are provided in Table 5 for demonstration purposes. The result of Breusch and Pagan Lagrangian multiplier test for random effects also shows that (random) individual effects are all insignificant. Overall, the results indicate that both fixed and random effects are insignificant and pooled OLS method is appropriate to estimate the econometric model. Table 6 presents results of the linear and log-linear model with pooled OLS method.

Robust estimates of both linear model and log linear model confirm statistical significant correlation between ARD and PAT as well as between DIV and PAT. The coefficient estimate of the KCI variable is not significant in both models. The adjusted R-square value and F statistics are higher for the log linear model. Therefore, for the rest of the paper the analysis will be performed using the log linear model. However, the high degree of correlation between DIV and ARD, as well as VIF value being greater than 5

Table 3. Correlation coefficients between average relatedness density, regional diversity and knowledge complexity index with patent applications (2010 and 2017)

	ARD	PAT	KCI	DIV
2010				
ARD	1			
PAT	0.242242 (0.303474)	1		
KCI	0.255847 (0.276261)	0.139947 (0.556217)	1	
DIV	0.894058 (1.08E-07)***	0.603824 (0.004814)***	0.203198 (0.390213)	1
2017				
ARD	1			
PAT	0.662002 (0.00023)***	1		
KCI	0.405549 (0.039833)*	0.215073 (0.291363)	1	
DIV	0.95364 (5.13E-14)***	0.79224 (1.41E-06)***	0.330189 (0.099473)*	1

causes a suspicion that the DIV variable captures the impact of ARD and that the coefficient of the ARD variable is negative, while it is expected that patent applications will be positively correlated with average relatedness density of the regions.

We therefore re-estimate the panel OLS model using the two variables independently: One with ln(ARD) and ln(KCI) as independent variables (Model 1) and the other with ln(DIV) and ln(KCI) as independent variables (Model 2).

Table 4. Checking for Multicollinearity using VIF

Variable	VIF	1/VIF	Variable	VIF	1/VIF
ARD	7.490	0.134	ln(ARD)	8.100	0.123
DIV	7.260	0.138	ln(DIV)	7.660	0.131
KCI	1.110	0.901	ln(KCI)	1.170	0.855
Mean VIF	5.290		Mean VIF	5.640	

Table 5. Fixed Effects Model

Dependent variable: PAT	Coefficient	Std. Err.	t-stat	p
ARD	-25.8696	11.99867	-2.16	0.056
KCI	0.451482	1.267211	0.36	0.729
DIV	90.40205	29.9886	3.01	0.013
Constant	-96.31539	113.7538	-0.85	0.417
Number of Obs.	= 46			
F-Stat (3, 10)	= 3.09			
Prob > F	= 0.0764			
R-Squared				
Within	= 0.4814			
Between	= 0.8700			
Overall	= 0.7362			
Diagnostic tests for model specification: F-test for fixed effects	Significance test statistic: F (32, 10)=0.15 Probability: 1.000			

The results are presented in Table 7.

Table 7 shows that when evaluated independently, ARD and DIV have a positive and significant effect on innovation. A 1% increase in ARD increases patent applications by

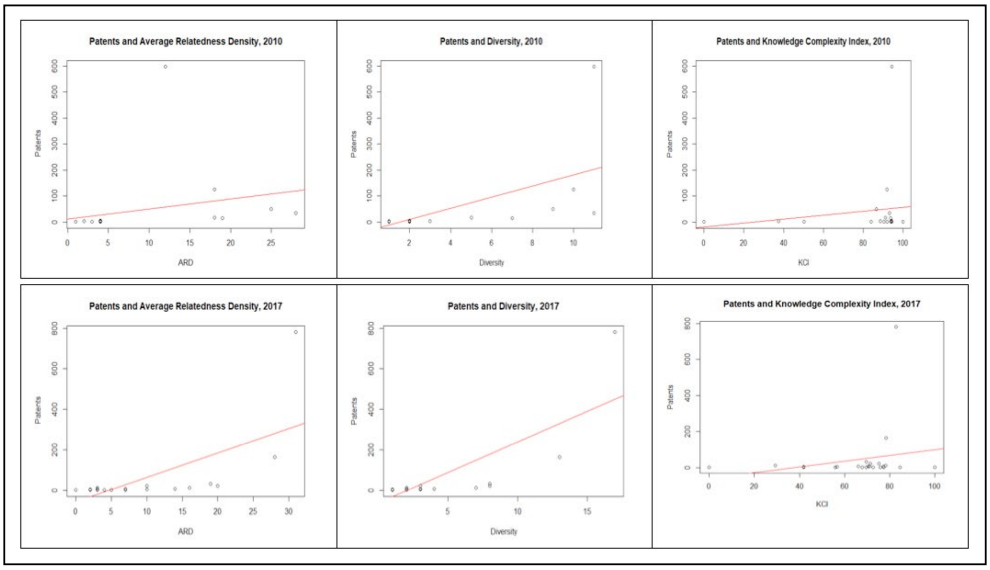

Figure 3. Relationship between average relatedness density, regional diversity and knowledge complexity index with patent applications (2010 and 2017) (2010 and 2017).

Source: OECD REGPAT database (OECD, 2020), own calculation.

Table 6. Panel OLS Estimation (Pooled OLS) with linear and log-linear models with clustered standard errors

LINEAR MODEL (Dependent variable: PAT)	Coefficient	Robust Std. Err.	t-stat	p
ARD	-22.327	4.690	-4.760	0.000
KCI	0.470	0.294	1.600	0.120
DIV	70.705	10.973	6.440	0.000
Constant	-57.105	15.395	-3.710	0.001
Number of Obs.	= 46			
F-Stat (3, 32)	= 23.29			
Prob > F	= 0.000			
R-Squared	= 0.7442			
LOG-LINEAR MODEL (Dependent variable: ln (PAT))	**Coefficient**	**Robust Std. Err.**	**t-stat**	**p**
ln(ARD)	-0.816	0.470	-1.740	0.090
ln(KCI)	0.123	0.411	0.300	0.767
ln(DIV)	2.433	0.467	5.210	0.000
Constant	0.542	1.671	0.320	0.747
Number of Obs.	= 44			
F-Stat (3, 40)	= 55.44			
Prob > F	= 0.000			
R-Squared	= 0.8432			

Table 7. Panel OLS Estimation (Pooled OLS) log-linear models with clustered standard errors

MODEL 1:	Coefficient	Robust Std. Err.	t-stat	p
ln(ARD)	1.565673	0.24803	6.31	0.000
ln(KCI)	-0.61723	0.454296	-1.36	0.184
Constant	1.629731	1.9748	0.83	0.416
Number of Obs.	= 44			
F-Stat (2, 31)	= 21.24			
Prob > F	= 0.000			
R-Squared	= 0.6241			
MODEL 2:	**Coefficient**	**Robust Std. Err.**	**t-stat**	**p**
ln(DIV)	1.712	0.154	11.090	0.000
ln(KCI)	-0.192	0.391	-0.490	0.626
Constant	1.083	1.710	0.630	0.530
Number of Obs.	= 44			
F-Stat (2, 41)	= 62.99			
Prob > F	= 0.000			
R-Squared	= 0.8209			

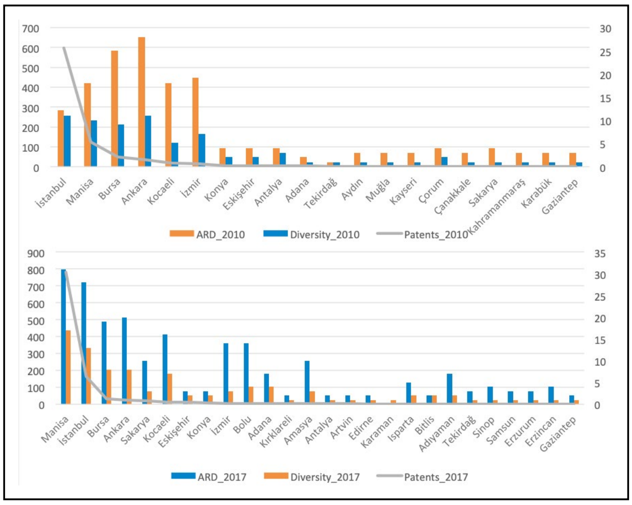

Figure 4. Patent applications, relatedness density and diversity of regions (2010 and 2017).

Source: OECD REGPAT database (OECD, 2020), own calculation.

1.5%. Similarly, a 1% increase in diversity increases patent applications by 1.7%. There is no relationship between complexity and patent applications. Overall, regions with high number of patents are also high with respect to diversity and relatedness (Fig. 4).

In addition to our baseline model using the pooled OLS regression analysis shared in the previous section, further econometric analyses are added to be able to control for the effects of other variables as well as regional and year fixed-effects on the patent numbers (log). Logarithms of GDP per capita (PCGDP) and human capital (HC) are added as control variables. The PCGDP variable was measured by using Turkey Regional Economic Dataset (Karaca, 2018). It shows the per capita GDP of regions by NUTS3 level at constant prices (2009 TL). The HC variable was measured by using "attained education level by provinces of population 15 years of age and over" data set (TUIK, 2019). The variable shows the share of people with an advanced level of education (graduates of universities, other higher educational institution, master, and doctorate) to the regional population with 15 years of age and over.

The results of the additional regression models are provided in the Table 8. In the first model, which includes only ARD as independent variable, a positive and significant impact of relatedness on regional innovation is indicated. The second model, whose results (Table 5) and interpretation had been previously provided, includes both ARD and KCI as independent variables. The model 3 only includes the control variables PCGDP and HC and shows a positive and significant effect of PCGDP on regional innovation. In the fourth and fifth models, all variables are included. The model 4 was estimated with a pooled OLS and indicates a positive and significant sign for the coefficient of the ARD variable. On the other hand, in the model 5 with regional and year fixed-effects, none of the variables has a significant impact on the patent applications.

To sum up, in all models, except for the fifth model, average relatedness density has a positive and significant effect on regional innovation. Accordingly, a 1% increase in the average relatedness density increases the number of patent applications by 1.39-1.56%. As far as the knowledge complexity is concerned, the coefficients are negative but insignificant in all models.

While there are changes in number of patent applications for individual cities, the ranking from highest to lowest number of patent applications did not change between 2010 and 2017. The highest number of patent applications in 2010 was in Istanbul, Manisa, Bursa, Ankara, Kocaeli and İzmir. In 2017, the cities with highest number of patent applications are, Manisa, İstanbul, Bursa, Ankara, Sakarya and Kocaeli. With the exception of İzmir and Sakarya, the five cities (İstanbul, Manisa, Bursa, Ankara and Kocaeli) are the cities with highest number of patent applications. Diversity in 2010 and 2017 show a similar ranking across cities. Cities with highest diversity in 2010 is Istanbul, Ankara, Manisa, Bursa, İzmir and Kocaeli and while in 2017 the list includes Manisa, İstanbul, Bursa, Ankara, Kocaeli and Bolu. With regards to average relatedness density, 2010 top list includes Ankara, Bursa, İzmir, Manisa, Kocaeli and İstanbul and 2017 top list includes Manisa, İstanbul, Ankara, Bursa, Kocaeli and İzmir.

5. CONCLUSION

In this paper we examine the knowledge space, average relatedness density and knowledge complexity of the regions and their correlations with regional innovativeness as measured by number of patent applications in Turkey for two different years: 2010 and 2017. Our aim is to map out the technology space by exploring proximity between technology pairs as well as understanding spatial distribution of relatedness density and knowledge complexity of technologies and correlation with patent applications. The results can be summarized under two subheadings:

Knowledge Space

Investigation of the knowledge space, we see that network ties across individual technology classes became dens-

Table 8. Models with additional control variables

Dependent variable: ln(PAT)	ARD (1)	ARD and KCI (2)	Control variables (3)	Full model (4)	Full model (FE) (5)
Constant	-0.7521952**	1.62989	-34.485**	-13.40406	39.49395
	(0.3499067)	(1.974665)	(13.71012)	(11.99596)	(24.07537)
	[0.039]	[0.415]	[0.017]	[0.272]	[0.111]
lnARD	1.432958***	1.56568***		1.390832***	0.7160408
	(0.2451715)	(0.2480293)		(0.3179437)	(0.6249297)
	[0.000]	[0.000]		[0.000]	[0.261]
lnKCI		-0.6172716		-0.6711447	-0.6318612
		(0.4542636)		(0.5747012)	(0.8581473)
		[0.184]		[0.252]	[0.467]
lnPCGDP			3.451049***	1.389935	-2.154569
			(1.239516)	(1.03274)	(1.703156)
			[0.009]	[0.188]	[0.215]
lnHC			-1.252101	-0.9953898	6.555681
			(0.987872)	(0.7155756)	(4.023366)
			[0.214]	[0.174]	[0.113]
Region Fixed Effects	No	No	No	No	Yes
Time Fixed Effects	No	No	No	No	Yes

Clustered standard errors are shown in parentheses (); P-values are shown in square brackets [ ]; Coefficients are statistically *significant at the α≤0.1 level, **significant at the α≤0.05 level and *** significant at the α≤0.01 level.

er over time and higher number of patent applications are within the denser part of the knowledge space map. Knowledge space of 2010 and 2017 indicates a movement into new technologies, leaving of the old ones, possibly making a conclusion that it is possible to make projections for future technological paths in Turkey. The results reveal that the number of patents and intensity of technology connections changed between 2010 and 2017 away from chemistry to electrical engineering, a more complex technology class. In 2017, complexity index of fields in electrical engineering was high, particularly for audio-visual technology, telecommunications, digital communication, basic communication processes and IT methods for management.

Patent Applications, Relatedness Density and Knowledge Complexity

In Turkey, we see considerable heterogeneity across the cities in relation to patent applications, relatedness density and knowledge complexity. Regression results reveal that diversity and relatedness positively affect regional innovativeness as measured by patent applications. Knowledge space reveals that there is a shift of patents to more complex technologies. Findings propose that it is reasonable to support diversity and relatedness.

The study is only a preliminary attempt to explore the distribution of knowledge across Turkey's regions and its connection with innovativeness. First, it is not possible to reach to strong conclusions with only two years of observations, 2010 and 2017. Furthermore, the unit of spatial analysis of this study was 81 NUTS3 regions in Turkey, representing cities. Relatively smaller geographical areas might be a problem with moderately low frequency of patent applications where there is a threat of losing observations in econometric estimates. Further studies should redefine space where it would be possible to assemble the data according to Turkey's 26 NUTS2 regions.

Second, what further studies should consider is to add more years, and additionally work with three to five year windows to capture larger number of patent applications. The problem of this paper is that we only use 2 years of patent data. Since the number of patent applications varies from year to year, it is suggested that further studies include more years and work with aggregated data with time windows.

Third, working with more years of patent data and grouping the data in time windows would likely to have significant implications for the knowledge space. In the current analysis, there is a considerable change in the knowledge space between 2010 and 2017. This difference between years may be due to the fact that in some technology classes there are hardly any patents or that some technologies may be present in one year and not available in the other year, which may make it difficult to observe the relatedness between technologies. This is also why there is a large fluctuation in KCI across the regions between the two years, where we do not expect such dramatic change in the complexity of an economy between two years within a same decade. Another drawback of working with two years is that it restricts the possibility of working with time lags and our ability of testing the hypothesis that lagged values of ARD and DIV would have impact on the patent applications. We would expect that ARD and DIV will only have an effect with a time lag, and not having an influence on innovation in the same year. Additionally, due to low patenting activity at regional scale, when measuring ARD, further studies can include not only the technologies in which a region is specialized (with RTA >1), but also include those with lower RTAs, such as RTA>0.5.

In summary, the results of the study should be interpreted with caveat due to limited number of observations. More data and aggregated time periods and regions are needed for further studies. Nevertheless, the paper reveals preliminary results that regional policies should focus on increasing diversity of industries and enabling conditions that potential new technologies in the region be close to the existing technological portfolio of the region. The paper supports the idea that smart specialization policy based on the relatedness framework is not a one size fits all policy and all regions ought to focus on their existing portfolios to draw new economic activities.

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REFERENCES

Asheim, B. T., Boschma, R., & Cooke, P. (2011). Constructing regional advantage: Platform policies based on related variety and differentiated knowledge bases. *Regional studies, 45*(7), 893-904. doi:10.1080/00343404.2010.543126 [CrossRef]

Balland, P. A. (2017). Economic Geography in R: Introduction to the EconGeo Package. *Papers in Evolutionary Economic Geography, 17*(09), 1-75. [CrossRef]

Balland, P. A., & Rigby, D. (2017). The geography of complex knowledge. *Economic Geography, 93*(1), 1-23. doi:10.1080/00130095.2016.1205947 [CrossRef]

Balland, P. A., Boschma, R., Crespo, J., & Rigby, D. (2019). Smart specialization policy in the European Union: relatedness, knowledge complexity and regional diversification. *Regional Studies, 53*(9), 1252-1268. doi:10.1080/00343404.2018.1437900 [CrossRef]

Balland, P. A., Rigby, D., & Boschma, R. (2015). The technological resilience of US cities. *Cambridge Journal of Regions, Economy and Society, 8*(2), 167-184. [CrossRef]

Boschma, R. (2014). Constructing regional advantage and smart specialisation: Comparison of two European policy concepts. *Italian Journal of Regional Science (Scienze Regionali), 13*(1), 51-68. [CrossRef]

Boschma, R. (2017). Relatedness as a driver of regional diversification: A research agenda. *Regional Studies 51*(3), 351-364. [CrossRef]

Boschma, R., & Frenken, K. (2006). Why is economic geography not an evolutionary science? Towards an evolutionary economic geography. *Journal of economic geography, 6*(3), 273-302. [CrossRef]

Boschma, R., Balland, P. A., & Kogler, D. F. (2015). Relatedness and technological change in cities: the rise and fall of technological knowledge in US metropolitan areas from 1981 to 2010. *Industrial and corporate change, 24*(1), 223-250. doi:10.1093/icc/dtu012 [CrossRef]

Çelik, N., Akgüngör, S., & Kumral, N. (2019). An assessment of the technology level and knowledge intensity of regions in Turkey. *European Planning Studies, 27*(5), 952-973. doi:10.1080/09654313.2019.1579301[CrossRef]

Cooke, P., Uranga, M. G., & Etxebarria, G. (1997). Regional innovation systems: Institutional and organisational dimensions. *Research policy, 26*(4-5), 475-491. doi:10.1016/S0048-7333(97)00025-5 [CrossRef]

European Commission. (2020a). *Smart Specialization Platform*. Retrieved from https://s3platform.jrc.ec.europa.eu/

European Commission. (2020b). *Smart Specialisation: Strengthening Innovation in Europe's Regions*. Factsheet, Smart Specialisation Platform, Regional and Urban Policy.

Foray, D., Goddard, J., Beldarrain, X. G., Landabaso , M., McCann, P., Morgan, K., . . . Ortega-Argilés , R. (2012). *Guide to Research and Innovation Strategies for Smart Specialisations (RIS 3)*. Smart Specialisation Platform, Regional Policy. European Commission.

Freeman, C. (1995). The 'national system of innovation' in historical perspective. *Cambridge Journal of Economics, 19*(1), 5-24.

Frenken, K., & Boschma, R. A. (2007). A theoretical framework for evolutionary economic geography: Industrial dynamics and urban growth as a branching process. *Journal of economic geography, 7*(5), 635-649. [CrossRef]

Frenken, K., Van Oort, F., & Verburg, T. (2007). Related variety, unrelated variety and regional economic growth. *Regional studies, 41*(5), 685-697. doi:10.1080/00343400601120296 [CrossRef]

Gezici, F., Yazgı-Walsh, B., & Kacar, S. (2017). Regional and structural analysis of the manufacturing industry in Turkey. *Annals of Regional Science, 1*(59), 209–230. doi:10.1007/s00168-017-0827-4 [CrossRef]

Gülcan, Y., Akgüngör, S., & Kuştepeli, Y. (2011). Knowledge generation and innovativeness in Turkish textile industry: Comparison of Istanbul and Denizli. *European Planning Studies, 19*(7), 1229-1243. doi:10.1080/09654313.2011.573134

Hidalgo, C. A., & Hausmann, R. (2009). The building blocks of economic complexity. *Proceedings of the National Academy of Sciences, 106*(26), 10570-10575. [CrossRef]

Hidalgo, C., Balland, P. A., Boschma, R., Delgado, M., Feldman, M., Frenken, K., . . . Zho, S. (2018). The principle of relatedness. In A. J. Morales, & et al. (EDS), *Unifying Themes in Complex Systems IX* (pp. 451-457). Cham: Springer Nature. [CrossRef]

Jacobs, J. (1969). The Economy of Cities. *New York: Vintage Books*.

James, G., Witten, D., Hastie, T., & Tibshirani, R. (2017). *An Introduction to Statistical Learning with Applications in R* (8 ed.). Springer Texts in Statistics.

Karaca, O. (2018). 50 Years of Regional Convergence in Turkey: New Data Set and Analysis for the Period 1960-2010. *Sosyoekonomi, 26*(35), 207-228. [CrossRef]

Kaygalak, İ. (2013). Türkiye sanayi coğrafyasında endüstriyel kümelenme ve bölgesel yoğunlaşma eğilimi. *Beşeri Coğrafya Dergisi, 1*(1), 67-81.

Kaygalak, İ., & Reid, N. (2016). The geographical evolution of manufacturing and industrial policies in Turkey. *Applied Geography, 70*, 37-48. [CrossRef]

Kogler, D. F., Rigby, D. L., & Tucker, I. (2013). Mapping knowledge space and technological relatedness in US cities. *European Planning Studies, 21*(9), 1374-1391. [CrossRef]

Kuştepeli, Y., Gülcan, Y., & Akgüngör, S. (2013). The innovativeness of the Turkish textile industry within similar knowledge bases across different regional innovation systems. *European Urban and Regional Studies, 20*(2), 227-242. [CrossRef]

Lundvall, B. Ä., & Johnson, B. (1994). The learning economy. *Journal of industry Studies, 1*(2), 23-42. doi:10.1080/13662719400000002 [CrossRef]

Maraut, S., Dernis, H., Webb, C., Spiezia, V., & Guellec, D. (2008). The OECD REGPAT Database: A Presentation. *OECD Science, Technology and Industry Working Papers*(2008/02).

Marshall, A. (1890). Principles of Economics. 1 (First ed.). *London: Macmillan*.

Martin, R., & Sunley, P. (2015). On the notion of regional economic resilience: conceptualization and explanation. *Journal of Economic Geography, 15*(1), 1-42. [CrossRef]

Maskell, P., & Malmberg, A. (1999). Localised learning and industrial competitiveness. *Cambridge journal of economics, 23*(2), 167-185.

Morgan, K. (1997). The learning region: institutions, innovation and regional renewal. *Regional Studies, 31*(5), 491-503. [CrossRef]

Neffke, F., Henning, M., & Boschma, R. (2011). How do regions diversify over time? Industry relatedness and the development of new growth paths in regions. *Economic geography, 87*(3), 237-265. [CrossRef]

Nelson, R. R., & Winter., S. G. (1982). An evolutionary theory of economic change. *Cambridge, Mass.: Harvard University Press*.

OECD. (2020). REGPAT database, January 2020.

Rigby, D. L. (2015). Technological relatedness and knowledge space: entry and exit of US cities from patent classes. *Regional Studies, 49*(11), 1922-1937. [CrossRef]

Rigby, D. L., Roesler, C., Kogler, D., Boschma, R., & Balland, P. A. (2019). Do EU regions benefit from smart specialization? *Utrecht University Papers in Evolutionary Economic Geography, 19*.

Romer, P. M. (1990). Endogenous technological change. *Journal of political Economy, 98*(5, Part 2), S71-S102. [CrossRef]

Schmoch, U. (2008). *Concept of a technology classification for country comparisons. Final report to the world intellectual property organisation (WIPO)*. WIPO.

Schumpeter, J. A. (1939). *Business cycles: A theoretical, historical, and statistical analysis of the capitalist process* (Vol. 1). New York and London: McGraw-Hill Book Company Inc.

Schumpeter, J. A. (1942). *Capitalism, Socialism and Democracy*. New York: Harper & Row.

Solow, R. M. (1956). A contribution to the theory of economic growth. *The quarterly journal of economics, 70*(1), 65-94. [CrossRef]

TUIK. (2019). *National Education Statistics Database, 2008-2019*. Retrieved 2021, from Education Statistics: http://www.tuik.gov.tr/

Whittle, A., & Kogler, D. F. (2019). Related to what? Reviewing the literature on technological relatedness: Where we are now and where can we go? *Papers in Regional Science, 99*(1), 97-113. [CrossRef]

Widuto, A. (2019). *European Regional Development Fund and Cohesion Fund 2021-2027*. European Parliamentary Research Service. European Parliament.