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The effects of regional capacity in knowledge recombination on production efficiency

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ABSTRACT

Knowledge recombination, combining knowledge existing (exploitation) or new knowledge capacity (exploration) for creating knowledge collaboration, is one of the important ways of achieving innovation. However, little has known about how the knowledge recombination types affect differently to production efficiency at a regional level. This study explores the relationship between the knowledge recombination types of exploitation and exploration and regional technical efficiency by using the empirical data sets combining EPO PATSTAT, Eurostat, and Cambridge Econometrics regional database. For this purpose, three stages of analysis have been deployed. Firstly, CPC co-occurrence network analysis and relative comparative advantage (RCA) measures are used to construct knowledge space and measure regional capacity. Then, using the stochastic frontier analysis, the production efficiencies of the European NUTS 2 regions are measured. With all estimated measures, the effects of both exploration and exploitation of knowledge recombination on regional production efficiencies are estimated. The results show the positive effect of exploration on regional production efficiency, which highlights the importance of extending the range and variety of knowledge bases.

1. Introduction

The importance of regional knowledge structure has continuously gained attention as an explanatory factor for innovation, economic performance, and productivity gains (Capello and Lenzi, 2015). Identifying the nature of knowledge cores across regions has become important to figure out region's competitive advantage in technological capabilities and restructuring of economies. Especially, studies have found that the competitive advantage is mainly due to region's respective capacity of producing high-value, complex, and tacit knowledge (Balland and Rigby, 2017; Lawson and Lorenz, 1999; Storper and Venables, 2004). Regions are therefore encouraged to build technological capacity by expanding knowledge stocks and developing novel knowledge with higher complexity.

In specific, technological changes in a geographical space involve dynamic process of generation and utilization of the knowledge base of an economy (Cooke et al., 1997; Kogler, 2015), such as recombination activities of knowledge. Indeed, innovations largely depend on the recombination of existing knowledge of the knowledge structure (Fleming, 2001; Nelson and Winter, 1982; Yayavaram and Ahuja, 2008). Knowledge can be generated from either combining technologies and knowledge that have never been combined before or exploiting already known combinations to solve new problems and innovate. The two recombinant activities are easily distinguishable because they differ in terms of required recombinant capabilities and face different challenges (Carnabuci and Operti, 2013). Thus, their impacts on economic performance and growth may also vary; however, questions concerning the relationship between these recombinant types of knowledge and regional production efficiency remain unanswered.

Most novel innovations originate by combining previously unconnected technologies (new recombination) or by reconfiguring and improving existing technological knowledge combinations (exploiting the recombination space) (Aharonson and Schilling, 2016). For example, at the firm level, firms' recombinant capabilities are a key

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source of firms' innovative performance (Carnabuci and Operti, 2013; Henderson and Clark, 1990; Yayavaram and Ahuja, 2008). At the regional level, by virtue of the knowledge space methodology, stochastic frontier analysis, and a newly updated patent database, it is now feasible to investigate the effects of explorative and exploitative capacity in recombination on production efficiency at the regional level.

Thus, this study explores how the regional type of technological recombination is associated with the regional production efficiency. For the empirical analysis, PATSTAT and regional socio-economic data of the European NUTS 2 level regions for the period between 1980 and 2014 are utilized. Using accumulated pan-European knowledge space and stochastic frontier analysis, each region's regional capability in new and exploitative recombination, and production efficiencies are measured. With these measures, the effect of recombination type on production efficiency is regressed to determine which type has a positive and significant relationship with production efficiency.

The remainder of this paper is structured as follows. Section 2 reviews the literature on knowledge recombination type, exploration, and exploitation, and the relationship between recombination type and production efficiency. Section 3 describes the methodology and data used in the analysis, and the results are presented in Section 4. Finally, the discussion and concluding remarks are provided in Section 5.

2. Literature review

2.1. Structural change in regional knowledge

The evolutionary perspective is fundamental to understanding the geographies of technological progress, dynamics, restructuring of economies, and economic growth. It is believed that regions transform through constant structural changes, and those changes are very often path-dependent on the stock of knowledge at a given place and time (Boschma et al., 2015). Pre-existing local knowledge sets and activities over time configurate both the present and future pathways of region's technological trajectories and variety of economic structures (Cooke et al., 1997; Kogler, 2015). In other words, regional transformations arise endogenously within the socio-economic system through the underlying process of continuous internal development of knowledge (Metcalfe et al., 2006).

This path- and place-dependent property of knowledge base has been identified by numerous studies. Those studies constructed a knowledge space built upon co-exporting product data or patent data to identify knowledge domains and to trace the evolving process of structural changes over time within a certain geographical scope. For example, Hidalgo et al. (2007) proved that countries seek out new industrial possibilities from existing sets of industrial capabilities. Then scholars also confirmed the same logic at regional level studies (Boschma et al., 2013), since sub-national level regions have more specific technological capabilities than those at the national level because capabilities are not easily moved even within the nation (Neffke et al., 2011). The evolution of local knowledge space over time depicted strong dependency on pre-existing knowledge profile: regions tend to diversify their economic or technological capabilities based on relatedness (Boschma et al., 2015; Kogler et al., 2017; Kogler et al., 2013).

Identifying the nature of knowledge cores across regions is therefore important to figure out region's competitive advantage and to find the best way forward while facing diverse technological possibilities and uncertainties (Balland et al., 2019). Studies have found that the competitive advantage of regions is due to their respective capacity of producing high-value, non-ubiquitous, elaborate, and tacit knowledge (Lawson and Lorenz, 1999; Storper and Venables, 2004), and Balland and Rigby (2017) revealed that as knowledge gains higher complexity, it becomes less spatially mobile, which gives the region a competitive advantage and results in divergence among cities. Complexity of knowledge can be described in terms of diversity of knowledge combination upon distinct and multiple components (Zander and Kogut, 1995), and Mewes and Broekel (2020) found that technological complexity measured by structural diversity (Broekel, 2019) contributes to regional economic growth.

Thus, the capability to expand knowledge cores and to develop knowledge from low complexity toward greater complexity is crucial to regions. Regions are encouraged to build new comparative advantages by initially exploiting related and existing knowledge domains. Then, regions should strive to develop new technologies with higher complexity than they already have produced (Balland and Rigby, 2017). Here, recombinant possibilities or remapping of linkages between knowledge components drive the dynamics of structural change of knowledge space in regions (Kogler et al., 2017).

However, while a lot of studies have focused on tracking the change of the shapes of knowledge space over time, relatively little attention has been paid to the underlying mechanism of how and through what activities regions diversify. Specifically, investigation on knowledge production practices operated within the region, such as knowledge recombinant activities, is required. Questions such as what type of combinations of technologies are more productive and how cities and regions can achieve efficient transition to diversification should be answered.

2.2. Knowledge recombination and its impact on production efficiency

Nelson and Winter (1982) stated that "innovation consists to a substantial extent of a recombination of conceptual and physical materials that were previously in existence" (p. 130). Most innovative outcomes are achieved either by combining knowledge in a completely novel manner or by reusing the already known or existing combinations for different applications (Fleming, 2001; Yayavaram and Ahuja, 2008). Consequently, studies have introduced two types of knowledge recombination: one is creating new technological combinations that have not previously been used, recombinant creation, and the other is reusing known combinations, recombinant reuse (Carnabuci and Operti, 2013). Levinthal and March (1993) referred to these as "exploration" and "exploitation", defined as "the pursuit of new knowledge, of things that might come to be known," and "the use and development of things already known" (p. 105), respectively.

The concept of knowledge recombination has often been discussed in firm level analysis, since a firm's recombinant capability affects its innovative performance and helps to secure its competitive position (Arthur, 2007; Kaplan and Vakili, 2015; Rosenkopf and Nerkar, 2001). According to the literature, firms' seeking new knowledge starts with the reuse of already existing knowledge combinations, and firms then often develop new combinations initially through incremental processes (Fleming, 2001; March, 1991). This is because exploitation of knowledge has been proven to secure certain returns to a firm and therefore reduces the risks and uncertainties. Since it is the refinement and expansion of existing capabilities, technologies, or applications, the results are mostly positive, proximate, and likely to be guaranteed (Audia and Goncalo, 2007). However, this repeated mechanism of learning, continuous exploitation of known combinations, would lead to decreasing returns due to the problems of overlooking distant times, distant areas, and failures and to obsolescence in the long run (Aharonson and Schilling, 2016; Levinthal and March, 1993).

On the other hand, most breakthrough innovations come from new recombination (Fleming, 2001). Innovative performance can be fully achieved by increasing recombination sets of knowledge that can be accessed (Ahuja et al., 2008), and the explorative approach facilitates the new breakthrough opportunities due to its extended variety of knowledge bases (Ahuja and Lampert, 2001). Linking distant and diverse sources increases creativity, which in turn creates breakthroughs and thus, brings economic wealth and social welfare (Audia and Goncalo, 2007; Kaplan and Vakili, 2015). However, although exploration enables the discovery of novel ideas, technologies, and solutions, it is not always positive in the short run due to high uncertainty in performance

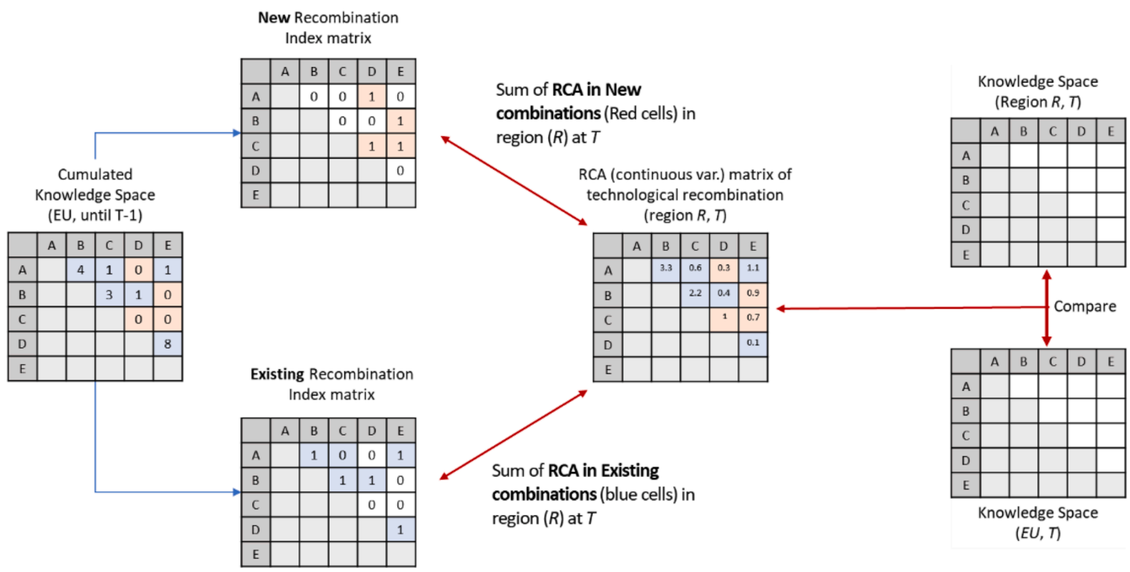

Fig. 1. Cycle of innovation and imitation.

(Aharonson and Schilling, 2016). In short, exploitation increases short-term productivity, but exclusively engaging in exploitation is not enough for long-term productivity. In contrast, exploration decreases short-term productivity, but it may result in greater long-term productivity and returns.

In terms of the effect on production efficiency, studies have argued that technological innovation spurs greater levels of productivity: technological change involving new ways of production increases productivity which shifts the production frontier outward. Mohnen and Hall (2013) illustrates some explanations on how innovation affects productivity, such as an introduction of a new product by a new production process or technology which engages new pool of demand and a process innovation which reduces production costs. Among them, the paper emphasized the degree of novelty of a given production innovation, because the more novel the product, the larger potential it has for success in the market. By the benefit of scale effects, it increases productivity. Also, a process breakthrough could lower costs even more that creates stronger growth (Duguet, 2006). Moreover, even when controlling for labor skill, higher innovation output and productivity are positively correlated (Crépon et al., 1998).

The emphasis on the degree of novelty or breakthrough-ness is based on the assumption that growth gains depend on innovation level. For example, small modifications, which are also generally recorded as innovation, may do not have significant effects on production efficiency. On the other hand, improvements such as altering an element of a product or a process would have large effects, since it raises the probability for a firm to create a new product or develop technological breakthroughs. In this regard, Duguet (2006) distinguished French manufacturing firms' innovation heights into incremental innovation and radical innovation and investigated whether their contribution to TFP growth differ. Incremental innovation includes improvement of a pre-existing product or process, and radical innovation incorporates creation of a new product or a process breakthrough. The results indicated that only radical innovations contribute to productivity growth.

In addition, radical innovations tend to rely on the degree of diversity and complexity of knowledge source or technological opportunities which are a key source of economic growth (Ahuja and Lampert, 2001; Ahuja et al., 2008; Carnabuci and Operti, 2013; Fleming, 2001). Consequently, they are more likely to generate important knowledge spillovers than increment innovations, so are likely to succeed in capturing gains from innovation. Further, disruptive innovations are more positively related to the economic gains when it is a tacit knowledge, while incremental innovations are more positively related to explicit knowledge (Hsiao et al., 2017; Lawson and Lorenz, 1999), which in turn indicates radical innovations are related to greater production efficiency growth.

Exploration and exploitation in this study can be identified as radical innovation and incremental innovation, respectively, discussed above. Because radical innovations, which come from a new way of producing that did not exist before, affect production efficiency by both the market demand and technological opportunities, we can expect that it is the exploration that facilitates production efficiency growth.

In the meanwhile, exploration and exploitation of knowledge have often been discussed in firm-level analysis, while only few attempts have been made to investigate regions' recombinant capabilities. Those studies were limited to analyzing the recombinant activities in micro-level firms within a specific region, rather than accounting on the region's knowledge space at meso-level (Rosenkopf and Nerkar, 2001). Therefore, this study aims to investigate the knowledge recombinant activities of a region using the knowledge space methodology and patent data to determine their effects on region's innovative performance.

3. Methods

3.1. Research design

To understand the relationship between knowledge recombination type and production efficiency, the overall analysis was conducted in three stages. First, regional knowledge space for each European NUTS 2 level region was constructed with patent data for every five years for the period from 1980 to 2014. We use Cooperative Patent Classification (CPC) codes, which is a joint classification system between USPTO and EPO, for technological classes. Knowledge space is depicted by a technology class co-occurrence matrix as shown in Fig. 1, and it illustrates the scheme for calculating regional capacity in the exploration and exploitation of region R in period T ($T \in [2,7]$).

On the left side of the figure, two index matrices are derived from cumulated knowledge space of EU until the period *T-1*. New recombination index matrix represents explorative combinations which are completely new, and existing recombination index matrix represents exploitative combinations which have existed already. For example, there are four new recombinant spaces where the two technologies had never co-occurred until the period *T-1* (combinations of A-D, B-E, C-D, and C-E). These four sets are coded 1 in the new combination matrix as a completely new recombination set compared to the cumulative knowledge space, and the others are coded 0. The same method was applied to existing recombination index matrix.

Then, the relative comparative advantage (RCA) of technological recombination in region R at T is measured to evaluate the region's knowledge exploration and exploitation capacity. First, we calculated the number of co-occurrences of the recombination sets identified in each index matrix and the number of co-occurrences of the whole pairwise sets in knowledge space both in region R and EU at period T. We then compared the numbers of co-occurrences of R to that of EU to estimate the region R's RCA in recombination against other regions in EU. The calculation of regions R's RR(RCA in Recombination) used herein is specified in Eq. (1):

$$RR(RCA\ in\ Recombination)_{ij} = \frac{S_{i,j,R} \Big/ \sum_i \sum_j S_{i,j,R}}{S_{i,j,EU} \Big/ \sum_i \sum_j S_{i,j,EU}} \tag{1}$$

where $S_{i,j,R}$ and $S_{i,j,EU}$ represent the number of co-occurrences of technology i and j in region R and EU, respectively. Lastly, region R's exploration capability and exploitation capability during period T are calculated as Eqs. (2) and (3), respectively:

$$Exploration_{R,T} = \frac{\sum_i \sum_j RR\ in\ New\ Recombination_{i,j,R,T}}{\sum_p IS_{p,R,T}} \tag{2}$$

$$Exploitation_{R,T} = \frac{\sum_i \sum_j RR\ in\ Existing\ Recombination_{i,j,R,T}}{\sum_p IS_{p,R,T}} \tag{3}$$

where *RR in New Recombination* is the RR measured in Eq. (1) for the new recombination sets, and *RR in Existing Recombination* is the RR for the existing recombination sets. $IS_{p,R,T}$ refer to region R's inventor share of patents listing technology i in period T compared to EU. Inventor share details were extracted from the address data for patents across NUTS 2 regions.

Using these measures, technical efficiency (TE) was measured using stochastic frontier analysis (SFA) to assess regional production efficiency. SFA is often used to identify efficiency (Cullinane et al., 2002) and produce relevant measures for testing hypothesis (Lee et al., 2015). With this approach, we can investigate whether exploration or exploitation contributes to the production efficiency under assumption of exhibiting the same quantity of input. In this respect, we firstly measure production efficiency of the region, then regress our key measures on it.

We apply the efficiency analysis instead of the production function approach, because we believe that the difference in efficiency between regions is due to the heterogeneity of the regions' knowledge structure, here focusing on the regional recombination capacity. We hypothesize that a local knowledge recombination capacity shapes the region's knowledge structure, and this makes a difference in the regional production efficiency.

As the distance between the frontier production function and regional technology level decreases, the region's TE increases. This study adopts Battese and Coelli (1995)'s SFA model and measures TE to capture the change in efficiency over time as follows:

$$Y_{R,T} = f\left(X_{R,T}; \beta\right) e^{v_{R,T} - u_{R,T}} \tag{4}$$

where $Y_{R,T}$ is the observed amount of output of region R at T, $X_{R,T}$ is a vector of region R's input set in period T, f is the production function, β is a vector of unknown parameters to be estimated, $v_{R,T}$ is an independent and identically distributed random variable that follows a normal distribution of the regression equation, and $u_{R,T}$ refers to the inefficiency of region R from the frontier production function. To reflect the fact that inefficiency is always above zero, $u_{R,T}$ is non-negative and follows a half-normal distribution.

For the production function f, the trans-log production function instead of Cobb–Douglas production function is used to account for complicated interactions between inputs because the latter assumes output as a log-linear combination of inputs, which is too simplified.

Table 1
A design of exogenous variables in SFA.

Model 1	*Model 2*	*Model 3*	*Model 4*
Exploration		Exploration	Exploration
	Exploitation	Exploitation	Exploitation
		Exploration × Exploitation	
			Exploration ratio

Thus, using the random effects time-varying production model and trans-log production function, Eq. (4) can be rewritten as Eq. (5):

$$lnY_{R,T} = \beta_0 + \sum_{m=1}^{3} \beta_m lnx_{mRT} + \sum_{m=1}^{3} \sum_{\substack{k=1,\\ k\geq m}}^{3} \beta_{mk} lnx_{mRT} lnx_{kRT} + v_{R,T} - u_{R,T} \tag{5}$$

where $X_{1,R,T}$ indicates the size of capital, $X_{2,R,T}$ indicates the size of cost, and $X_{3,R,T}$ indicates the size of the labor pool of region R at T. Gross fixed capital (GFC), compensation of employees, and number of employees were used for each variable. $Y_{R,T}$ refers to Gross value-added (GVA) of region R at T. Then, the TE is calculated as in Eq. (6):

$$TE_{R,T} = e^{-u_{R,T}} = \frac{Y_{R,T}}{f\left(X_{R,T}; \beta\right) e^{v_{R,T}}} \tag{6}$$

Lastly, there is a vector of exogenous variables that influence the level of the regional technical inefficiency. We assume that the inefficiency of region R, $u_{R,T}$, is a function of each region's recombination capacity which consists of $\boldsymbol{Exploration}_{R,T}$ and $\boldsymbol{Exploitation}_{R,T}$ as shown in Eq. (7):

$$u_{R,T} = f\left(Exploration_{R,T},\ Exploitation_{R,T}\right) \tag{7}$$

Table 1 shows four models we used for the function of each region's technical inefficiency. Model 1 and 2 includes the exploration and the exploitation capacity, respectively. In Model 3 and 4, we put the two types of recombination capacity together in the same model with considering the interaction effect. The interaction term and the ratio of exploration capacity are used in Model 3 and 4.

3.2. Data

The analysis requires two types of data sets: patent data, which can identify technological fields and where the technologies were invented, and regional socio-economic data. The patent data are from EPO's PATSTAT as it contains all patents applied for through the EPO and detailed information on year of application, inventors, assignees, technological fields, and citations. In this study, technological fields are split using CPC codes at the four-digit level. The advantage of using CPC is that it contains new categories under section Y of new technological developments and crossover technologies (Leydesdorff et al., 2017). In addition, technologies are separated by NUTS 2 regions based on the information on inventors' residence.

Moreover, socio-economic data for SFA analysis are from Eurostat and Cambridge Econometrics. The variables used in herein include Gross Domestic Products (GDP), Gross fixed capital (GFC), compensation of employees (CE), and number of employees (NE). In addition, the

Table 2
Descriptive statistics of variables ($N = 1306$).

Variable	Mean	Std. Dev.	Min	Max
Y: Ln(GDP)	3.605	0.727	1.707	6.345
X1: Ln(GFC)	8.906	0.712	6.865	11.681
X2: Ln(CE)	9.760	0.767	7.627	12.409
X3: Ln(Emp)	6.514	0.692	4.407	8.712
Exploration	0.1044	0.0595	0.0000	0.7869
Exploitation	1.0654	0.5668	0.1935	6.2371
Exploration ratio	0.0960	0.0420	0.0000	0.2639

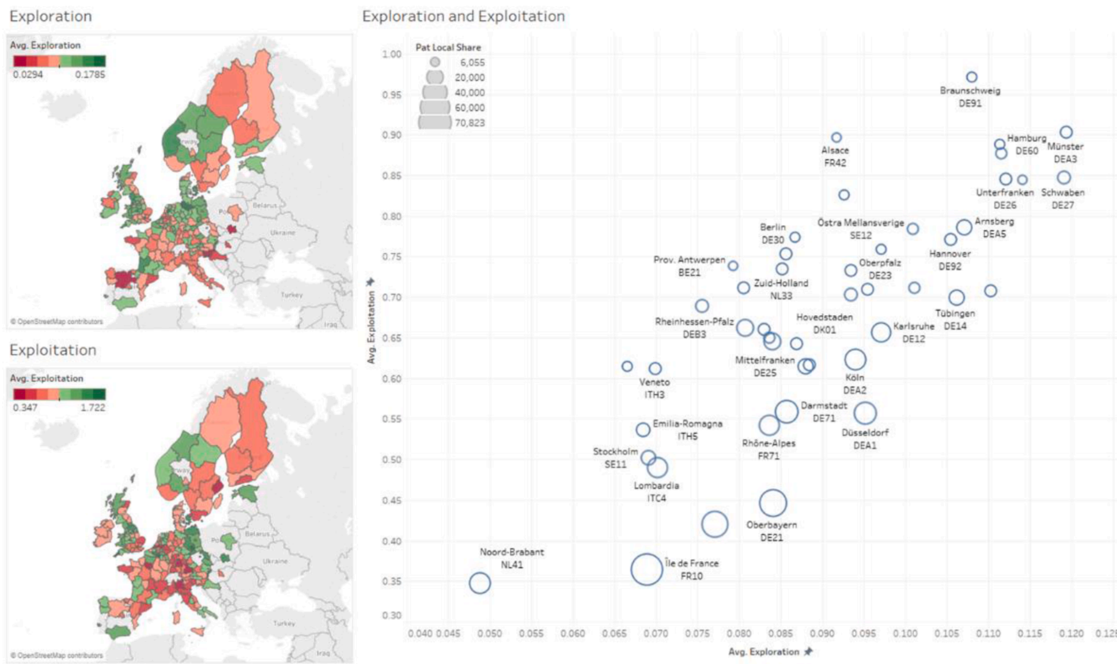

Fig. 2. Regional recombination capacity and patenting.

Table 3
Results of the estimation of SFA without inefficiency effect (Sample using 5-year window).

	Model 1	*Model 2*	*Model 3*	*Model 4*
Frontier				
X1 (Ln_Labor)	0.067***	0.785***	0.309*	0.153
	(0.011)	(0.200)	(0.127)	(0.137)
X2 (Ln_Cost)	0.601***	1.400***	0.448*	0.590**
	(0.015)	(0.313)	(0.175)	(0.201)
X3 (Ln_Capital)	0.308***	-2.250***	-0.427**	-0.312
	(0.016)	(0.387)	(0.159)	(0.206)
$X1^2$		-0.060***		0.073***
		(0.016)		(0.021)
$X2^2$		-0.040*		-0.048
		(0.016)		(0.036)
$X3^2$		0.146***		-0.091*
		(0.022)		(0.043)
X1*X2			-0.050*	-0.134***
			(0.022)	(0.036)
X2*X3			0.056***	0.208**
			(0.013)	(0.073)
X3*X1			0.026	0.028
			(0.025)	(0.053)
Const.	-5.446***	-0.245	-2.186***	-2.901***
	(0.050)	(0.813)	(0.450)	(0.479)
Observations	1,306	1,306	1,306	1,306
Number of NUTS2	216	216	216	216
Degree of Freedom	7	10	10	12
AIC	-1797.748	-1116.054	-1863.732	-1881.363
BIC	-1761.525	-1064.307	-1811.984	-1819.266

Note: Standard error is in parenthesis. Stars (*, **, and ***) indicate significance at $p < .05$, $p < 0.01$, and$p < 0.001$, respectively.

time variables are included as dummy variables.

For the purpose of this study, an analytic sample is created as follows. First, the sample is restricted to those patents in which the filing year for the first application was between 1980 and 2014. Then, the period is grouped into every five years to smooth annual fluctuations in patent applications for regions and codes (Kogler et al., 2017). Second, the sample includes only observations that have all values in the variables in use. Third, the analysis uses standardized values for exploration and exploitation. Descriptive statistics of the variables for the regression models are reported in Table 2.

4. Results

With technology class co-occurrence matrices of regions for every five years, average exploitation and average exploration are calculated for measuring regions' recombination capacity. Fig. 2 shows the regions' recombination capacity for exploration and exploitation. The x- and y-axis represent the average exploration and exploitation, respectively, and the patent share of regions is also illustrated. The scatter plot shows that exploitation and exploration have a positive linear relationship. Further, despite their relatively smaller share in the number of patents, regions such as Munster, Hamburg, and Schwaben showed their strength in both exploration and exploitation. According to this analysis, regions from Germany (DE) tend to have high capabilities in knowledge recombination.

Table 3 shows the estimation results of SFA without inefficiency effect. Four different frontier functions were compared to find the best production efficiency estimation model. Model 1 is purely estimated by putting the three inputs of labor, capital, and cost into the frontier function without variants of the input variables. Model 2 was estimated by putting the square values of the inputs. Model 3 considers the interaction between inputs, and Model 4 considers everything. The model fit can be known through the change in AIC and BIC values. Model 2 had the lowest fit based on Model 1 as a reference, and the fitted values are increased in Models 3 and 4. Model 4 is the best fit among the four, therefore we adopt Model 4 as a basic frontier function in further analyses.

The stochastic frontier function is estimated by using Model 4 above, and then the TE for each region over the years is calculated. Fig. 3 shows the highest 35 regions and the lowest 35 regions in rank of average TE. The "Blue Banana" shape, which indicates the main economic development and innovation centers in Europe (Hospers, 2003) also appears on the map on the left side of the figure.

The results of the estimation of SFA equation are reported in Table 4. In all models, regional- and periodic-specific fixed effect are included. According to the results, while exploitation has a positive association with the inefficiency of the region (Model 3), exploration has a negative association (Models 1, 3, and 4). The synergy between Exploration and

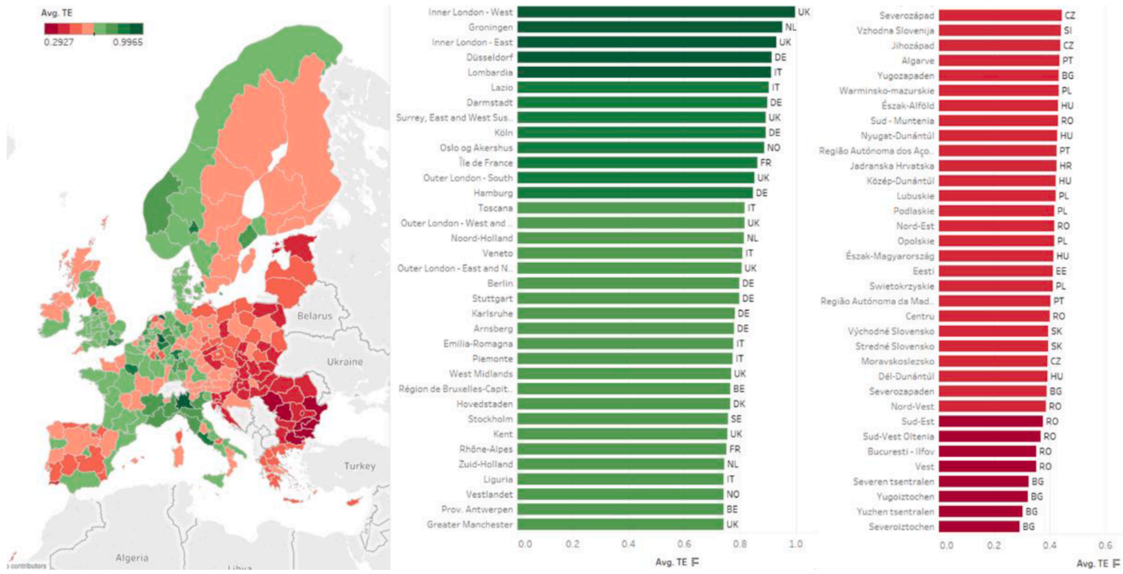

Fig. 3. Regional production efficiency.

Table 4
Results of the estimation of SFA equation (Sample using 5-year window).

	Model 1	*Model 2*	*Model 3*	*Model 4*
Frontier				
X1 (Ln_Labor)	0.240	0.0436	-0.111	0.0326
	(0.201)	(0.181)	(0.318)	(0.163)
X2 (Ln_Cost)	0.673***	0.703***	0.900***	0.673***
	(0.231)	(0.226)	(0.375)	(0.222)
X3 (Ln_Capital)	-0.399	-0.225	-0.298	-0.181
	(0.221)	(0.218)	(0.587)	(0.214)
$X1^2$	0.0761***	0.0786***	0.0574	0.0753***
	(0.0304)	(0.0283)	(0.0399)	(0.0265)
$X2^2$	-0.0296	-0.00142	-0.0184	0.00397
	(0.0390)	(0.0415)	(0.164)	(0.0416)
$X3^2$	-0.0693	-0.0827	-0.0548	-0.0835
	(0.0461)	(0.0466)	(0.0501)	(0.0462)
X1*X2	-0.152***	-0.194***	-0.127	-0.195***
	(0.0400)	(0.0399)	(0.174)	(0.0390)
X2*X3	0.169***	0.133	0.105	0.125
	(0.0855)	(0.0859)	(0.219)	(0.0847)
X3*X1	0.0381	0.103	0.0761	0.111***
	(0.0612)	(0.0573)	(0.184)	(0.0551)
Const.	-3.091***	-3.346***	-3.528***	-3.356***
	(0.585)	(0.561)	(0.525)	(0.573)
Inefficiency (U sigma)				
Exploration	-0.116***		-0.212***	-0.259***
	(0.132)		(0.536)	(0.268)
Exploitation		0.368	0.824*	0.406
		(0.215)	(1.745)	(0.234)
Exploration × Exploitation			-0.161***	
			(1.492)	
Ratio of Exploration				0.0857***
				(0.457)
Const.	-2.982	-3.729	-3.484	-3.562
	(2.363)	(2.991)	(13.97)	(3.971)
Regional FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	1,306	1,306	1,306	1,306
Number of NUTS2	216	216	216	216

Note: Standard error is in parenthesis. Stars (*, **, and ***) indicate significance at $p < .05$, $p < 0.01$, and $p < 0.001$, respectively.

Exploitation was negatively significant ($\beta = -0.161$, $p < 0.001$) in Model 3. Moreover, the ratio of exploration also negatively affects the inefficiency of the region ($\beta = 0.0857$, $p < 0.001$) in Model 4. In this result,

Table 5
Results of the estimation of SFA equation (Sample using 3-year window).

	Model 1	*Model 2*	*Model 3*	*Model 4*
Frontier				
X1 (Ln_Labor)	0.167	0.0610	0.0986	0.178
	(0.322)	(0.125)	(0.128)	(0.275)
X2 (Ln_Cost)	0.587	0.668***	0.633***	0.562***
	(0.338)	(0.158)	(0.171)	(0.215)
X3 (Ln_Capital)	-0.221	-0.256	-0.194	-0.202
	(0.214)	(0.155)	(0.159)	(0.205)
$X1^2$	0.0791	0.0363***	0.0745***	0.0813***
	(0.0442)	(0.0169)	(0.0214)	(0.0242)
$X2^2$	-0.00787	-0.0679***	-0.0114	-0.0113
	(0.0323)	(0.0230)	(0.0302)	(0.0301)
$X3^2$	-0.0998***	-0.122***	-0.108***	-0.110***
	(0.0448)	(0.0315)	(0.0339)	(0.0406)
X1*X2	-0.206***	-0.116***	-0.205***	-0.213***
	(0.0405)	(0.0255)	(0.0303)	(0.0308)
X2*X3	0.165	0.226***	0.168***	0.180***
	(0.0923)	(0.0499)	(0.0626)	(0.0658)
X3*X1	0.103	0.0773***	0.117***	0.107***
	(0.0627)	(0.0372)	(0.0415)	(0.0461)
Const.	-3.180***	-3.096***	-3.294***	-3.171***
	(1.617)	(0.424)	(0.440)	(0.985)
Inefficiency (U sigma)				
Exploration	-0.0284**		-0.0656***	-0.00322**
	(0.104)		(0.103)	(0.170)
Exploitation		0.257***	0.339***	0.293
		(0.123)	(0.139)	(0.152)
Exploration × Exploitation			-0.0666	
			(0.0798)	
Ratio of Exploration				0.0707**
				(0.262)
Const.	-3.830	-3.098	-3.464	-3.532
	(34.83)	(3.807)	(3.038)	(2.615)
Regional FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	2,226	2,226	2,226	2,226
Number of NUTS2	216	216	216	216

Note: Standard error is in parenthesis. Stars (*, **, and ***) indicate significance at $p < .05$, $p < 0.01$, and $p < 0.001$, respectively.

Exploration is clearly proved as a plus factor for the regional production efficiency, whereas Exploitation is not. Furthermore, it was found that the two competencies have a stronger trade-off effect than the complementary effect, showing that the strengthening of the Exploitation capacity inevitably leads to the weakening of the Exploration capacity.

We also proceeded a robustness check with another sample by using 3-year window setting. Although 5-year window is widely accepted setting in relevant research, this should be clearly stated as it influences the sample size and estimation result. The result confirms that our findings do not change depending on the length of time period (See Table 5).

5. Discussion and conclusion

This study investigates regional capacity in knowledge recombination and its impact on the regional production efficiency of regions in Europe. As knowledge is accumulated, knowledge diversity and novel recombination of knowledge become new drivers for economic growth, especially for sustainable long-term regional development in advanced regions. However, questions regarding the relationship between recombination capacity and production efficiency at a regional level have remained unanswered. In this regard, this study specifies regional types of technological recombination into exploration, which is completely new recombination of knowledge, and exploitation, which is recombination of already existing knowledge, and measures their effects on regional production efficiency in NUTS 2 level European regions from 1980 to 2014.

For the analysis, the knowledge space of regions is constructed based on technology class co-occurrence matrices with patent data retrieved from EPO's PATSTAT, and a region's RCA for each recombination type is calculated. TE is then estimated with a stochastic frontier analysis model using a random-effects time-varying production model and a trans-log production function with socio-economic data. Lastly, the full model regarding the exogenous regional knowledge recombination type is considered to estimate the production frontier and to calculate each region's production efficiency.

The results in Tables 4 and 5 show that new recombination, which is explorative activities, had a positive and significant influence on production efficiency, while exploitation of knowledge had no significance or even negative effect. In other words, regions with strength and that focus on the exploration of knowledge tend to gain greater production efficiency and faster growth in terms of production efficiency.

Subsequently, this result is a supportive extension of the arguments of a series of regional diversification studies. Previous studies on technological diversification and its effect on regional economic growth show that the more diversified and complex the knowledge base, the more competitiveness and growth the regions achieve (Balland and Rigby, 2017; Boschma, 2017; Kogler et al., 2017). In addition, a more diverse knowledge base tends to prevent exploitative activities but enhances a region's capacity to innovate through explorative recombinant activities (Carnabuci and Operti, 2013). As the result of this analysis proves that explorative recombination has a significant positive effect on regional production efficiency, and since the explorative approach extends the range and variety of knowledge bases to facilitate new breakthrough innovations (Ahuja and Lampert, 2001; Ahuja et al., 2008), this study supports the logic of regional diversification and economic growth. Thus, to achieve regional growth through enhancing production efficiency, explorative research needs to be promoted.

This study contributes by providing implications for regional innovation policy. Previous studies have noted the importance of knowledge structure and technological diversification and their effect on innovation in the region (Boschma et al., 2013; Lawson and Lorenz, 1999; Storper and Venables, 2004). However, they have failed to consider how new knowledge is effectively created and expanded upon and how it affects innovation and production efficiency growth. This study brought such discussion from the knowledge management field within the firm level to the geographical regional level by considering regional recombinant capacity in the process of innovation and production efficiency with the estimation of regional knowledge capacity and technical efficiencies of regions. Although reconfiguration of existing knowledge combinations costs less and secures returns on effort, completely new recombination is the factor that leads to production efficiency.

Thus, regional policies should be strategically designed to understand a region's knowledge structure, diversify technologically through an explorative knowledge production mechanism, and expand based on relatedness. Thinking of path-dependent nature of knowledge, exploitative knowledge production is more preferred because of its less uncertainty and greater efficiency. In this respect, regional policy should provide enough motivation for local inventors or firms to develop the new technology. More importantly, it should address long-term regional development roadmap so that the newly developed local knowledge can be settled down successfully. To do so, the newly explored local knowledge is better to be something that can be easily attached to the existing local knowledge structure, and this should be addressed based on the diagnosis on local knowledge structure. Moreover, by confirming that explorative combinatorial knowledge dynamics is significant, means for collaborative and collective learning for explorative search of knowledge within a region should be considered. This is also needed to be supported by regional policy to enhance more collaborative partnership between local agents. Especially, collaboration between industry, academia, and government can create a significant synergy effect, and the government should play the role as a broker between the two.

The importance of explorative knowledge recombination capacity to generate new knowledge should be emphasized even more, especially for regions with high levels of knowledge accumulation, as decreasing returns to scale from focusing on known knowledge combinations occur, and the regions have a large potential to expand their knowledge domains they can access for long-term economic growth.

However, this study has some limitations. First, the analysis applied a dichotomous classification of regional knowledge recombination, and second, the dependent variable, production efficiency, is limited to TE. Therefore, future research may apply more specific classifications of knowledge recombination types, such as new, low-, and high-related recombination. In addition, sectors or industries can be split up, for example, recombination effects in the manufacturing and service sectors. In our econometric estimation, spatial effects could be only controlled through regional dummy due to the complexity of our model such as imbalance panel. Furthermore, variables such as total factor production efficiency or technical progress can be applied. Finally, as exploration appears to be significant for production efficiency, future research can investigate knowledge spillovers transferred between regions.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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