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Abstract

Existing studies on regional diversification highlight the importance of local path dependencies and related competences. However, little attention has been paid to other factors potentially contributing to diversification processes. Foremost, this concerns the role of R&D policy. This study investigates the relation between R&D policy and regional technological diversification in German labor market regions from 1996 to 2010. We find no evidence for proactive R&D policies, as subsidized R&D projects do not promote regional technological diversification. In contrast, R&D subsidies' allocation is rather risk-averse with subsidies being more likely allocated to already established technologies and those related to region's technology portfolio.

Keywords

Regional Diversification; Innovation; Policy; R&D Subsidies; Relatedness

JEL-Codes

O31; O33; O38

1 Introduction

Regional diversification has recently received increasing attention at the political agenda. Prominently, *Smart Specialization* has been implemented as a European wide innovation policy tool to promote diversification in regions (Foray et al., 2011). The arguments for political guidance of regional diversification are obvious. Successful countries and regions in terms of productivity, innovation and economic growth are rather diversified (Hidalgo and Hausmann, 2009; Tacchella et al., 2012; Balland and Rigby, 2017). Diversification protects against cognitive lock-ins and exogenous shocks. The ability to permanently diversify into new fields is therefore key for regions' economic success (Grabher, 1993; Tödtling and Trippl, 2005; Martin and Sunley, 2006; Frenken et al., 2007; Boschma, 2015).

Besides its role in public policy, regional diversification has also received increasing attention in conceptual and empirical studies. Inspired by the pioneering works of Hidalgo et al. (2007) and Frenken et al. (2007), Neffke et al. (2011) particularly confirm that regions do not randomly diversify into new activities. Instead, new activities are more likely to emerge in regions when being related to existing capabilities (Neffke et al., 2011; Rigby, 2013; Boschma and Capone, 2015; Boschma et al., 2015; Essletzbichler, 2015). This process has been conceptualized as 'regional branching', i.e. related diversification (Boschma and Frenken, 2011).

Interestingly, this idea of regional branching has only indirectly entered the policy debate on diversification. Smart Specialization acknowledges the notion of related variety and builds on the increasing evidence that related diversification is the rule rather than the exception by specifically promoting strategic diversification into related activities (McCann and Ortega-Argilés, 2013). However, empirical studies on regional diversification have been surprisingly silent about the relation of R&D policy and related regional diversification (Boschma and Gianelle, 2014). Apart from single case studies (Coenen2015), there is no systematic analysis of governmental R&D support schemes in terms of allocation and effect from the perspective of related diversification. Put differently, although regional diversification has found its way into public policy, the relation between both remains largely unclear.

The present paper tackles this research gap by addressing two research questions: Does R&D policy support technological diversification in regions? Is R&D policy effective in doing so and helps in the adaptation or creation of new R&D activities in regions? While the first question is associated with the allocation of public R&D subsidies, the second specifically addresses policy's impact on regional diversification.

Our empirical approach builds on a panel dataset for 141 German labor market regions covering the period from 1996 to 2010. Patent data is used as an indicator for regional R&D activities. We focus on R&D subsidies as one crucial tool of R&D policy and merge information on publicly subsidized R&D projects with this patent data.

The results suggest that R&D subsidies in Germany are allocated to technologies, which have already been successful in the past. Accordingly, the subsidization of R&D projects in Germany rewards proven success and thereby reacts to past developments. We find no evidence for policy supporting related diversification by allocating R&D subsidies to related, but non existing technologies. Regarding the effect of the subsidies, our impact analysis does not reveal any effect of R&D subsidies on the diversification of regions into (regionally) new technologies.

The remainder of the study is organized as follows: Section 2 gives an overview of the existing literature on regional diversification and R&D policy. The introduction of the empirical data is subject to section 3. Our empirical approach is presented in section 4 and our results are part of section 5. The discussion of our results follows in section 6. Section 7 concludes the paper.

2 R&D policy and regional diversification

R&D policy programs are justified by knowledge creation and innovation being important production factors that lead to economic growth. However, knowledge creation suffers from strong market failures (Nelson, 1959; Arrow, 1962; McCann and Ortega-Argilés, 2013). Not only are innovation activities below a social optimum in general, but they are also unevenly distributed across national and regional economies (Marshall, 1890; Jacobs, 1969; Jaffe, 1989; Jaffe et al., 1993; Audretsch, David, B.; Feldmann, 1996; Florida, 2005; Balland and Rigby, 2017; Akcigit et al., 2017). Given the relevance of innovation for economic development and growth, this uneven geography of innovation calls for R&D policies (Tödtling and Trippl, 2005).

In the past, R&D policy tried to reduce regional gaps in innovation activities by selecting a number of promising technologies that are to be supported and subsequently funds are awarded in form of competitive bidding (Tödtling and Trippl, 2005). The German BioRegion program is a prominent example in this respect Dohse (2000). While such an approach may yield a relatively efficient support allocation, it usually does not help in reducing spatial variance in innovation activities, as only those regions will receive support that are already successful in the selected technologies. Frequently, the same regions dominate technological development in many areas and such allocation may therefore rather manifest existing spatial heterogeneity. Moreover, this approach does not consider regions' specific economic and innovation-related situations, which in many cases resulted in supported innovation activities being just loosely connect to regional capabilities (Tödtling and Trippl, 2005; Foray et al., 2011). In some instances, policy support was successful in promoting specific areas, however, these lack any regional embeddedness and appear to be 'cathedrals in the desert' (Boschma and Gianelle, 2014) with limited impact on regional growth.

In light of these experiences, scholars increasingly argued in favor of giving up such 'one-size-fits-all' approaches. Instead the individual situation of regions has to be taken into greater consideration in R&D policy (Tödtling and Trippl, 2005). The EU's Smart Specialization strategy is a prominent example of such a new policy approach. The policy's aim is to foster (technological) diversification around regions' core activities linking technological growth opportunities to the unique individual technological R&D capabilities of regions (Foray et al., 2011; McCann and Ortega-Argilés, 2013).

Roots of the Smart Specialization concept can be found in the recent literature on regional diversification, which shows that diversification is crucial for long-term growth and that it does not take place on a random basis. Concerning the first, diversification yields a number of positive externalities. First, diversification positively relates to the level of income highlighting that diversification is an important step in climbing the ladder of economic development (Imbs and Wacziarg, 2003). Second, the existence of R&D activities in related fields sparks synergies between local R&D domains increasing the exploitation and experimentation of technological opportunities (Foray et al., 2011). Third, diversified regions are less likely to run into the trap of cognitive lock-ins (Grabher, 1993). Fourth, diversification is expected to protect against exogenous shocks, because of a portfolio effect (Frenken et al., 2007).

Diversification does not occur randomly. Hidalgo et al. (2007) were among the first investigating how nations diversify into new products. They show that nations are more likely to diversify into new export products, which are related to their existing product portfolio. Assuming that capabilities do not easily move within a country, Neffke et al. (2011) adopted and transferred this approach to the regional level. By relying on information about products of Swedish manufacturing firms, they show that new industries do not emerge randomly across space. Rather, they are more likely to emerge in regions where related capabilities are already existing. Essletzbichler (2015) confirms this for industrial diversification in US metropolitan areas. Similar results are obtained by Boschma et al. (2013) for the export profile of Spanish regions. By comparing the impact of relatedness for different spatial levels, the authors also show related industries playing a more crucial role at the regional compared to the national level. Rigby (2013) and Boschma et al. (2015) analyze regional branching processes based on the emergence of new technologies in US metropolitan areas. Both find that technology entries are positively and exits are negatively correlated with their relatedness to regions' technology portfolios.

Technological relatedness is therefore a crucial driver of regional diversification, which is not detached from local contexts, but rather depends on the availability of localized capabilities. The recombination of related pieces of knowledge is thereby particularly effective due to optimal cognitive distance (Cohen and Levinthal, 1989; Nooteboom, 2000; Nooteboom et al., 2007). Moreover, recombining related pieces of knowledge drives incremental improvements, reinforcing existing trajectories and the accumulation of knowledge over time in space (Dosi, 1982; Fleming and Sorenson, 2001; Nooteboom et al., 2007; Castaldi et al., 2015). Hence, new technologies are more likely to emerge out of locally existing related technologies, rather than out of unrelated or geographically distant ones.

This links the concept of related diversification to the Smart Specialization policy: Successful development is more probable when it builds on regions' unique capabilities and when it does not simply copy approaches from elsewhere. According to Boschma and Gianelle (2014), successful development implies developing (diversify) into distinctive new areas of specialization, whereby these areas of specialization should 'draw on local related resources' (p. 17 Boschma and Gianelle, 2014). Crucially, regional diversification suffers from similar, but also different market failures as R&D in general. To shift R&D activities into new fields requires the purpose and the risk to explore new knowledge yet outside a region's core activities. Actors need to estimate the social value of a certain kind of activity and its resulting benefits. Hausmann and Rodrik (2003) describe this as a self-discovery process. Often, self-discovery is the experimental result of entrepreneurial activities. In case of failure, these entrepreneurs take the risks and fully bear the cost of investments. Is the discovery process, however, successful positive externalities will occur. Third parties will likely follow which have not payed the full amount of costs. These reasons reduce the desired level of local renewing, i.e. diversification (Rodrik, 2004). Thus, it can be assumed that most of these problems will be considerably smaller in case of diversification into related technologies. Nevertheless, due to the inherent uncertainty of the process and its results even related diversification is likely to remain below a socially optimal level.

Accordingly, in resemblance of the Smart Specialization strategy, related diversification provides a promising way of informing policy makers about economic and technological potentials of regions' future diversification. In light of its benefits outlined above, it moreover allows for evaluating existing R&D support schemes with respect to their contribution to (related) diversification. This has however rarely been done in the literature so far. An exception being the study by Coenen et al. (2015). It investigates opportunities, barriers and limits of regional innovation policy aiming at the renewal of mature industries. The authors show for the case of the forest industry in North Sweden that regional innovation policy can accompany the process of regional diversification by supporting the adoption and creation of related technologies. Systematic evidence, however, is missing in the literature.

The present study seeks to address this gap by analyzing existing R&D policy from the perspective of the regional diversification framework. We concentrate on one of the most important and frequently used instruments of R&D policy, namely project-based R&D subsidies (Aschhoff, 2008). It is crucial to point out that the considered R&D subsidies schemes are neither regional policies nor really designed to support technological diversification activities. However, R&D subsidies are awarded to organizations in particular locations and hence contribute to the development of regional R&D activities (Broekel, 2015). The type of subsidies considered in this study are designed to financially support individual and collaborative R&D activities. They are targeted at innovative self-discovery processes (Hausmann and Rodrik, 2003), inter-organizational knowledge exchange as well as adaptation activities (Broekel and Graf, 2012), which are central underlying mechanisms of technological diversification. Hence, while this policy tool may not be explicitly designed for supporting regional technological diversification, it has a significant potential of being effective in this manner.

In addition, in contrast to most other policy instruments, project-based R&D subsidies can be very precisely targeted. For instance, they can be restricted to specific organizations (location, size, industry), to specific fields (technologies, sectors), to particular modes of R&D (individual or joint), and policy can decide about starting dates and time period of support. Consequently, the tool does not only has the potential to stimulate regional diversification in general. At the same time, it offers significant fine-tuning possibilities to address specific regional circumstances and needs (e.g., in terms of timing, technological focus). In the context of the paper, we are particularly interested if it (intentionally or unintentionally) already facilitates related diversification. For instance, when policy seeks to advance a specific technology by awarding (through competitive bidding) R&D subsidies in this field, organizations with related knowledge can be expected to have more novel ideas than organizations specialized in this field. At the same time, their relatedness allows these organization to better understand the actual technological requirements in this field and come up with more feasible solutions than organizations with an unrelated background (Nooteboom, 2000). Both aspects tend to increase the likelihood of subsidization. Accordingly, current subsidies allocation procedures may (unintentionally) favor applications from organizations with related backgrounds even when the programs are not specifically designed to take relatedness into account.

In the remainder of the study, we investigate the potential impact of R&D subsidies on regional diversification and related diversification. More precisely, we analyze if subsidies are targeted at technologies that underachieve in regions and hence help regions to potentially diversify into these fields. It is also checked if subsidized technologies are related or unrelated to regions' technological portfolio. In addition to studying the allocation of R&D subsidies, their impact on regional (related) diversification is evaluated as well.

3 Data

For our analysis, we focus on the most recent years covered by our data (1996-2010). In a common manner, we rely on patent data to approximate invention activities at the level of technologies and regions (Boschma et al., 2015; Rigby, 2013). Despite well-discussed drawbacks (Griliches, 1990; Cohen et al., 2000), patents entail detailed information about the invention process such as the date, location, and technology. We use the OECD REGPAT and Citations Database, which cover patent applications from the European Patent Office. On the basis of inventors' residences, patents are assigned to 141 German labor market regions as defined by Kosfeld and Werner (2012).

Technologies are classified according to the *International Patent Classification (IPC)*. The IPC summarizes hierarchically eight classes at the highest and more than 71,000 classes at the lowest level. We aggregate the data to the four-digit IPC level, which differentiates between 630 different technology classes. The four-digit level represents the best trade-off between a maximum number of technologies and sufficiently large patent counts in each of these classes.

The so-called *Foerderkatalog* of the German Federal Ministry of Education and Research (BMBF) serves as a source for information on R&D subsidies of individual and joint R&D projects (Broekel and Graf, 2012). Note that only a small fraction of these R&D projects qualify as place-based policy intervention, e.g. the *BioRegio* program (Dohse, 2000). Although not having an explicit geographical focus, these projects are likely to exert non-intended regional effects. Thus, we include all R&D projects into our analysis. The *Foerderkatalog* lists detailed information on granted individual and joint R&D projects from 1960 onward. It has been used in a number of existing studies (Broekel and Graf, 2012; Broekel et al., 2015a,b; Cantner and Koesters, 2012; Fornahl et al., 2011). Among the information are grants' starting and ending dates, the location of the executing organization as well as a technological classification code called *'Leistungsplansystematik' (LPS)*. The LPS is a classification scheme developed by the BMBF and consists of 22 main classes. The main classes are, like the IPC, dis-aggregated into more fine-grained sub-classes, which comprises 1,395 unique classes at the most detailed level.

4 Indicators of R&D policy, regional diversification and relatedness

4.1 R&D policy

In order to address our main research question, we link R&D subsidies and regional diversification in our empirical framework. Such an approach requires matching R&D subsidies and patent data. As there are no official concordance tables, we applied a manual matching to relate LPS to IPC classes. Given their different purpose, it is not possible to link all LPS classes to the IPC and vice versa. In total, 416 out of 1,395 LPS have been linked to 97 unique IPC classes at the four-digit level. For each of the 97 IPC classes, we counted the number of subsidized projects P assigned to region i in class k:

$$R\&D\ PROJ_{i,k} = \sum_{i,k} P_{i,k} \tag{1}$$

Additionally, the dataset allows us to distinguish between individual and joint R&D projects subsidized by the Federal Government. Previous studies have shown that this distinction clearly affects the results (Fornahl et al., 2011; Broekel, 2015). We use this information to construct $INDIV\ R\&D$ (individual R&D projects) and $JOINT\ R\&D$ (joint R&D projects) in the same fashion as $R\&D\ PROJ$ but controlling for the type of project:

$$INDIV\ R\&D_{i,k} = \sum_{i,k} P_{i,k}\ indiv_{i,k} \tag{2}$$

and

$$JOINT\ R\&D_{i,k} = \sum_{i,k} P_{i,k}\ joint_{i,k} \tag{3}$$

with *indiv* and *joint* being 1 if the subsidized project $P_{i,k}$ is an individual or a joint project respectively and 0 otherwise.

4.2 Measuring diversification and relatedness

Preceding studies primarily use the revealed comparative advantage (RCA) to measure diversification (Hidalgo et al., 2007; Boschma et al., 2015). We refrain from this approach for four reasons. First, the RCA is identical to the location quotient and thus represents a measure of regional specialization more than an indicator of regional diversification. Second, being a relative measure, the RCA allows technologies to (artificially) 'emerge' in a region without any increase of invention activities. For the RCA to rise, it is sufficient for patents or citations to decrease in other regions. Third, the RCA is normalized at the regional and technology level, which is similar to the inclusion of regional and technology fixed effects in panel regression, which will be done in the empirical analysis. Fourth, explaining *successful* regional diversification by the regional co-occurrence of *successful* technologies can lead to severe endogeneity problems.

We therefore rely on forward citations of patents as an alternative measure of regional diversification. Unlike raw patent counts, patent citations represent regions' relevance (or success) as knowledge sources for subsequent inventions in specific technologies (Hall et al., 2005). Successful diversification DIV is indicated by patents in a particular technology not receiving any citations $CIT_{i,k,t}$ in the previous period $t-1$ and a positive number of citation in t:

$$DIV_{i,k,t} = CIT_{i,k,t} \quad if \quad (CIT_{i,k,t} > 0 \ \wedge \ CIT_{i,k,t-1} = 0) \tag{4}$$

We follow the literature in constructing the relatedness variable as a density measure (Hidalgo et al., 2007; Rigby, 2013; Boschma et al., 2015; Essletzbichler, 2015). In this context, density shows how well technologies fit to the regional technology landscape by means of technological relatedness. Its construction includes three steps.

First, we measure technological relatedness between technologies. The literature suggests four major approaches: (i) classification-based (Frenken et al., 2007; Castaldi et al., 2015), (ii) input-output linkages (Essletzbichler, 2015), (iii) spatial co-occurrence (Hidalgo et al., 2007; Neffke et al., 2011) and (iv) co-classification (Engelsman and van Raan, 1994; Breschi et al., 2003). We follow Breschi et al. (2003) and measure technological relatedness between technologies (patent classes) based on their co-classification pattern. The cosine similarity finally gives us a measure of technological relatedness between each technology pair.

Second, we determine which technologies belong to regions' technology portfolios at a given time. Straightforwardly, we use citation counts with positive numbers indicating the presence of a technology in a region.

Third, on this basis we estimate a density measure as follows (Hidalgo et al., 2007):

$$DENSITY_{i,k} = \frac{\sum_m x_m \ \rho_{k,m}}{\sum_m \rho_{k,m}} * 100 \tag{5}$$

with ρ indicating technological relatedness between technology k and m, while x_m being equal to 1 if technology m is part of the regional portfolio

($CIT > 0$) and 0 otherwise ($CIT = 0$). $DENSITY_{i,k}$ weights regions' technology portfolio with its relatedness to the focal technology. As a result, we obtain a 141 x 630 matrix providing for a density measure of relatedness for each of the 630 technologies in all 141 regions.[1]

4.3 Control variables

Knowledge spillover from adjacent regions can potentially affect regional diversification processes in a focal region. To account for these potential spatial neighboring effects, we consider the summed number of patents in technology k of all neighbors j of region i:

$$PAT\ NB_{i,k} = \sum_{j,k} PAT_{j,k} NB_{i,j} \quad with \quad i \neq j \tag{6}$$

with $PAT_{j,k}$ representing the number of patents in region j in technology class k. $NB_{i,j}$ is spatial weight taking the value 1 if region i and j share a common border and 0 if not.

Hidalgo et al. (2007) demonstrate that diverse regions have more opportunities within the local product space to move activities into new fields compared to highly specialized regions. That is why we consider regional diversity $DIVERSITY_i$ as an explanatory variable which we control for. $DIVERSITY$ is defined as the number of technologies with positive citation counts $CIT_{i,k}$.

Population density (POP_i), the number of regional patents ($REG\ PAT_i$)

[1] We also measured technological relatedness based on the spatial co-occurrence of technologies with RCA ≥ 1 yielding similar results.

and the focal technology's number of patents at the national level ($TECH\ PAT_k$) function as control variables for potential size effects. Additionally, we incorporate regional, technology and time fixed effects to account for time invariant unobserved heterogeneity.

Due to strong fluctuations in patent and citation counts, we apply a moving window approach in all analyses, which implies that all annual values of the considered variables in the time period 1996-2010 are estimated on the basis of a focal year t and its prior four years $t-4$. All explanatory variables are considered in time lags with respect to the dependent variable. We do not observe any notable changes using lags of three to seven years, which seem to be the theoretical minimum and maximum. Hence, we decided to lag all explanatory variables by five years, except for POP due to data availability. Table 1 lists all variables, table 2 entails the summary statistics and table 3 reports the correlation matrix.

Table 1: List of variables

CIT = Number of citations
PAT = Number of patents
DIV = Diversification, i.e. emergence of a new technology at the regional level
DENSITY = Relatedness density measure indicating the 'fit' of a technology in a region
R&D PROJ = Number of subsidized R&D projects
INDIV R&D = Number of subsidized individual R&D projects
JOINT R&D = Number of subsidized joint R&D projects
PAT NB = Number of patents in neighboring regions
REG PAT = Total number of patents in a region
POP = Population density
DIVERSITY = Number of technologies with CIT > 0
TECH PAT = Total number of patents in a technology

Table 2: Summary statistics

Statistic	Mean	St. Dev.	Min	Max
CIT	0.423	2.787	0.000	241.880
PAT	1.725	9.771	0.000	937.570
DIV	0.080	0.272	0	1
DENSITY	12.673	20.570	0.000	100.000
R&D PROJ	0.033	0.548	0	61
INDIV R&D	0.018	0.378	0	61
JOINT R&D	0.016	0.331	0	40
PAT NB	6.824	25.720	0.000	1,233.790
REG PAT	683.804	1,341.490	0.000	13,376.910
POP	404.484	376.357	39.000	2,473.750
DIVERSITY	55.478	70.690	0	394
TECH PAT	153.042	344.466	0.000	5,829.400

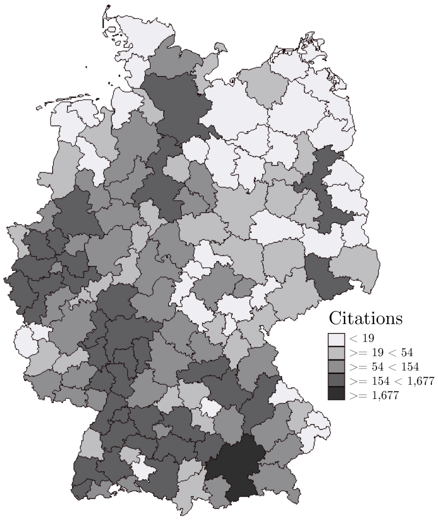
Table 3: Correlation matrix

	1	2	3	4	5	6	7	8	9	10	11	12
CIT	1											
PAT	0.740	1										
DIV	0.090	0.090	1									
DENSITY	0.300	0.290	0.130	1								
R&D PROJ	0.080	0.140	0.020	0.060	1							
INDIV R&D	0.050	0.100	0.020	0.040	0.810	1						
JOINT R&D	0.080	0.120	0.020	0.060	0.740	0.190	1					
PAT NB	0.380	0.420	0.090	0.310	0.040	0.020	0.050	1				
REG PAT	0.270	0.250	0.100	0.620	0.070	0.040	0.060	0.160	1			
POP	0.120	0.140	0.120	0.330	0.050	0.040	0.040	0.070	0.420	1		
DIVERSITY	0.240	0.220	0.120	0.730	0.060	0.030	0.050	0.220	0.870	0.450	1	
TECH PAT	0.270	0.310	0.110	0.250	0.050	0.030	0.050	0.600	0.090	0	0.150	1

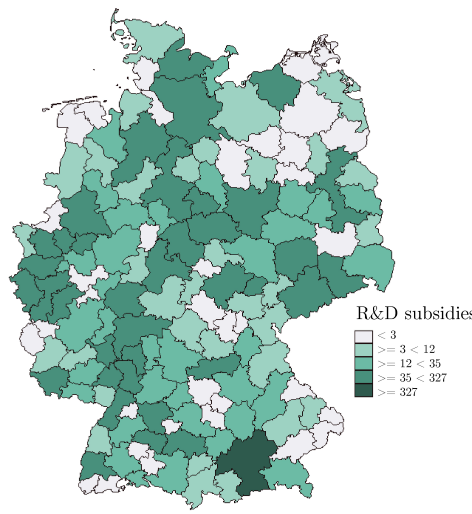
5 Results

5.1 The allocation of R&D subsidies

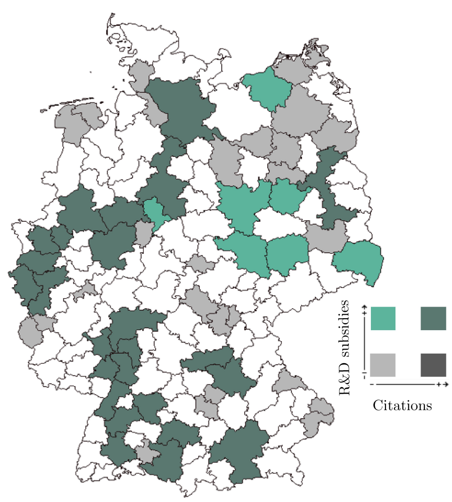
We first explore the allocation of R&D subsidies to regions and technologies in Germany. Opposed to the spatial distribution of invention activities (fig. 1(a)), the allocation of R&D subsidies (s. fig. 1(b)) does not exhibit any visual pattern. Invention activities show a clear tendency to cluster in space. This visual perception is confirmed by a significant Moran's I value of 0.132^{**}. They are mainly concentrated in urban regions along the Rhine river, the South and some parts of Northern Germany. Comparing the maps suggests a strong overlap of highly inventive regions and those receiving R&D subsidies. However, it appears to be the case that R&D policy also targets regions with rather moderate invention activities. Figure 1(c) highlights this by combining information on invention activities and the allocation of R&D subsidies. In addition, less inventive regions in East Germany receive strong R&D support as well. While these maps are informative, it should be pointed out that they are aggregated over all technologies and hence are influenced by regional variation in industrial structures.



(a) Invention activities



(b) R&D subsidies



(c) Relationship between R&D subsidies
and invention activities
(only the four extreme cases are colored)

Figure 1: Invention activities and R&D projects in German labor market regions 2006-2010

Table 4 compares characteristics of subsidized with non-subsidized technologies. A simple t-test reveals that subsidized technologies patent more and receive more citations than the group of non-recipients. Additionally, recipients are, on average, more related to the local technology portfolio and are situated in a more inventive environment.

Table 4: Mean and t-test results of subsidized and non-subsidized observations

	Subsidized	Non-subsidized	p-val
CIT	2.660	0.620	***
PAT	14.010	2.830	***
DENSITY	40.620	21.950	***
PAT NB	39.480	22.030	***

*p<0.05; **p<0.01; ***p<0.001

To systematically investigate the allocation of project based R&D subsidies, we apply a negative binomial regression model, as the dependent variable *R&D PROJ* is a count variable.

Table 5 shows the results for the allocation of R&D subsidies. Note that the number of observations is just 205,155, because we only considered IPC classes which have been matched with the LPS. *CIT* is positive and statistically significant indicating a higher chance of technologies to receive R&D

support when their patents are strongly cited. We interpret large citation counts as these technologies being already well-established in that region for some time. It implies that existing strength of regions are rewarded. However, it needs to be pointed out that the coefficient of CIT, expressed as odds ratio, has a relatively small effect size.

Table 5: Allocation of R&D subsidies

	Y = R&D PROJ	
	(1)	(2)
CIT_{-5}	0.01322***	0.06910***
	(0.00189)	(0.01188)
$DENSITY_{-5}$	0.00850***	0.00846***
	(0.00058)	(0.00058)
CIT_{-5} * $DENSITY_{-5}$		−0.00062***
		(0.00013)
PAT NB_{-5}	0.00070***	0.00063***
	(0.00018)	(0.00018)
REG PAT_{-5}	0.00001	0.00002
	(0.00001)	(0.00001)
POP_{-1}	0.00062	0.00062
	(0.00062)	(0.00062)
$DIVERSITY_{-5}$	−0.00411***	−0.00431***
	(0.00044)	(0.00044)
TECH PAT_{-5}	0.000003	−0.000001
	(0.00002)	(0.00002)
Observations	205,155	205,155

*p<0.05; **p<0.01; ***p<0.001
All models with region, technology and time fixed effects.

$DENSITY$ is statistically significant and obtains a positive sign. It signals that R&D subsidies are more likely allocated to technologies related to the regional technology portfolio. Accordingly, subsidies in related technological fields are relatively easier accessible than those in unrelated fields. This confirms our argument in section 2 of relatedness being advantageous in the allocation process of subsidies. The two significantly positive coefficients of CIT and $DENSITY$ suggest that the German policy of project based R&D subsidization is rather risk averse. It subsidizes either existing strength, or technologies that are related to regions' technological portfolio.

In the second model, we add the interaction term of CIT and $DENSITY$, which obtains large values when subsidized technologies are established and related. The term has low values when the technology is not established and unrelated. Interestingly, the interaction term gains a significantly negative coefficient, which seems to suggest that policy is supporting unrelated diversification. However, it turns out that the interaction term is difficult to interpret because of CIT being dominated by zero values. We run additional models on the basis of different subsamples ($CIT = 0$ vs. $CIT > 0$, $DENSITY > mean(DENSITY)$ vs. $DENSITY <= mean(DENSITY)$, $R\&D\ PROJ > 0$ vs. $R\&D\ PROJ = 0$, etc.).[2] The robust outcome of this exercise was that CIT and $DENSITY$ are greatly independent of each other and do not exercise a joint influence on subsidies allocation. Hence, policy is either awarding established technologies or related ones, with the latter being independent of whether they represent

[2] The results can be obtained from the authors upon request.

diversification possibilities or not.

$PAT\ NB$ indicates that technologies' probability of funding increases when they are located in an inventive regional neighborhood. This is in line with the findings of Broekel et al. (2015b). These authors show that regional clustering with other organizations active in similar technologies increases the likelihood of R&D subsidization.

The allocation of R&D subsidies is unrelated to POP suggesting that R&D policy does not favor urban regions. The level of invention activities in a region ($REG\ PAT$) is also insignificant. Note however that significant portions of both variables' effects might already be captured by CIT.

5.2 The impact of R&D subsidies on the technological diversification of regions

We evaluate the effect of public funding on regional diversification by applying linear regression models with region, technology and time fixed effects to explain technology-specific regional citation numbers. The dependent variable DIV limits the analysis to observations with the potential of technological diversification in t. That is, we concentrate on technologies in regions characterized by zero citations in $t-1$.[3]

Table 6 summarizes the empirical results. We estimate four different models. The first specification is the base model and includes $DENSITY$

[3] We also used the national average as a selection criterion and the RCA as an alternative measure for regional diversification, which however does not change the results significantly. These results can be obtained upon request from the authors.

and all control variables but excludes *R&D* $PROJ$. In line with the literature (Rigby, 2013; Boschma et al., 2015), relatedness ($DENSITY$) is found to play a positive and significant role in the process of regional technological diversification of German regions. $DENSITY$ remains statistically significant and positive throughout all models, which suggests that regions are more likely to obtain positive citation counts in technologies with no or uncited patents in $t-1$ that are related to their technology portfolio.

The same applies to the inventive output of neighboring regions ($PAT\ NB$). Being in spatial proximity to regions successful in a particular technology, makes diversification into this technology more likely. In line with the literature on spatial knowledge spillover (Jaffe et al., 1993), our results can be interpreted as a confirmation of their effectiveness. However, in contrast to most studies in this context confirming their relevance for general innovative output (Bottazzi and Peri, 2003), we confirm their impact on technological adaptation.

In addition to this, some regional size effects are observable: Interestingly, regions with many patents ($REG\ PAT$) are less prone to see technological diversification. The reason is that these regions are already well diversified and hence have less need and resources for additional diversification. This result relates to the findings of Imbs and Wacziarg (2003). A similar explanation holds for the variable $TECH\ PAT$, as the significantly negative coefficient confirms that large technologies have less (remaining) opportunities to emerge regionally. This is strengthened by the significantly negative coefficient of $DIVERSITY$ indicating that regions with many established technologies are less likely to experience additional diversification.

Table 6: Regional diversification and the impact of R&D projects

	Y = DIV			
	(1)	(2)	(3)	(4)
DENSITY_{-5}	0.004***	0.005***	0.006***	0.005***
	(0.0003)	(0.001)	(0.001)	(0.001)
$\text{R\&D PROJ}_{-5}$		0.016	0.022	
		(0.014)	(0.015)	
$\text{R\&D PROJ}_{-5}$ * DENSITY			−0.0003	
			(0.0002)	
$\text{INDIV R\&D}_{-5}$				0.010
				(0.012)
$\text{JOINT R\&D}_{-5}$				0.024
				(0.030)
PAT NB_{-5}	0.007***	0.004***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
REG PAT_{-5}	−0.00003***	−0.00005**	−0.00005**	−0.00005**
	(0.00001)	(0.00002)	(0.00002)	(0.00002)
POP_{-1}	−0.0003	−0.00003	−0.00003	−0.00003
	(0.0002)	(0.0003)	(0.0003)	(0.0003)
DIVERSITY_{-5}	−0.001***	−0.001*	−0.001*	−0.001*
	(0.0001)	(0.0003)	(0.0003)	(0.0003)
TECH PAT_{-5}	−0.0003***	−0.0002***	−0.0002***	−0.0002***
	(0.0001)	(0.00004)	(0.00004)	(0.00004)
Observations	1,215,115	176,932	176,932	176,932
Adjusted R^2	0.102	0.127	0.127	0.127

*p<0.05; **p<0.01; ***p<0.001
All models with region, technology and time fixed effects.
Standard errors were clustered at the regional and technology level.

Including R&D subsidies as additional explanatory variable (*model II*) limits the number of observations further to those technologies for which patent data and subsidies data are matched (see section 3). However, the results for the control variables are almost unaffected. Only $DIVERSITY$ is less significant, but the coefficient and sign are robust. The other control variables' coefficients keep their signs and (in-)significances.

When evaluating R&D subsidies' effects, endogeneity may arise due to selection bias (Busom, 2000; David et al., 2000). The previously identified differences between subsidized and non-subsidized technology-regions seem to support this view (see section 5.1). We therefore employ instrumental variable panel regression using the number of subsidized projects in a particular technology at the national level for instrumenting the corresponding regional numbers (Koski and Pajarinen, 2015). While the instrument fulfills the necessary requirements, the IV regression does not yield results different from those obtained when using simple linear panel regression. The variable of interest, $R\&D\ PROJ$, remains insignificant in all specifications. We therefore refrain from presenting the instrumental variables regression results and show instead that of the linear panel regression in table 6.[4]. While gaining a positive coefficient, $R\&D\ PROJ$ is insignificant. Accordingly, we do not find a significant contribution of R&D subsidization on technological diversification in German regions.

Relatedness makes diversification more likely and easier. We argued in section 2 that in line with the idea of the Smart Specialization policy of the EU, R&D subsidies may be more effective when they support the diversification into related technologies. In order to test this idea, we interact $R\&D\ PROJ$ with $DENSITY$ in model three. However, the coefficient of the interaction variable is negative and insignificant implying that project-

[4]The results for the instrumental variables approach can be obtained from the authors upon request.

based R&D subsidies do not contribute to regional diversification in general and related diversification in particular. This may be an outcome of the allocation of R&D subsidies discussed above. Technological diversification is less frequently subsidized than existing strength and hence, the amount of subsidies invested into such endeavors might simply be to small to detect an effect.

In model four, we distinguished between individual and joint R&D projects. It has been shown R&D subsidies' effects on inventive outcomes are primarily related to subsidized joint projects, as firms do not only benefit from additional monetary resources but also from the induced inter-organizational collaboration (Fornahl et al., 2011; Broekel, 2015). In contrast to these studies, our results do not confirm a difference between subsidies for individual and joint projects. Both coefficients, although positive, remain insignificant.

Before the results' implications are discussed, we have to point out a number of shortcomings of the present study. Most importantly, this concerns the consideration of just one type of policy intervention: R&D subsidies. While this is a crucial policy tool, it is not the only one. For instance, the establishment of public research facilities might impact the regional technology portfolio to a much larger degree than the here studied subsidies. Moreover, we exclusively consider R&D subsidies schemes of the German national government. Regional authorities but in particular the EU use similar tools (e.g. EU-Framework Programs), which, however, follow different allocation strategies (Broekel et al., 2015b). In addition to considering and comparing different policy schemes, future studies should also expand the empirical analysis to the firm level and consider longer time spans in order to test the robustness of our results.

6 Discussion and policy implications

Our empirical analysis focused on the allocation patterns of R&D subsidies and their impact on regional diversification processes. It thereby directly contributes to the debate on the Smart Specialization strategy of the European Union as part of the Europe 2020 agenda. According to this strategy, R&D policy should promote the process of regional diversification. More precisely, Smart Specialization implies that policy does not intervene randomly, but particularly encourages related diversification (Foray et al., 2011; Boschma and Gianelle, 2014).

While (related) diversification is empirically well investigated (Hidalgo et al., 2007; Rigby, 2013; Boschma et al., 2015; Essletzbichler, 2015), little attention has been paid to the role of R&D policy in this context (Boschma and Gianelle, 2014). Hence, it is largely unclear if and if so how R&D policy can impact (related) regional diversification. The present studied addressed this issue with an empirical study on the technological diversification of German regions.

Our empirical results for the allocation of R&D subsidies show that they are more likely awarded to established technologies suggesting that R&D subsidies are not used for facilitating regional diversification processes. While R&D subsidies may not explicitly intended to support such processes, the result still signals a risk averse R&D policy. Existing technological strengths are rewarded and existing regional technological profiles are manifested. This clearly contrasts the current EU Smart Specialization strategy, which aims at developing new technological fields and facilitating regional diversification. The strategy acknowledges the importance of entrepreneurial processes and ‘creative destruction’ (Foray et al., 2011), which however requires policy to allow “*projects to fail and disappear [as it is] an important part of the process of creative destruction*" Aubert et al. (2011, p. 67). This study's results reveal that the German project-based R&D subsidization does not take such risks. It rather seeks to minimizes failure of investments by sustaining already existing development paths. Pro-actively engaging in technology emergence or adaptation appears to be not part of the subsidization strategy.

We suspect that this behavior is related to the competitive character of the allocation process. As policy needs to justify public investment decisions (Cantner and Koesters, 2012; Aubert et al., 2011), reactive strategies are likely to emerge. When evaluating applications, applicants’ and applications’ quality are relatively easy to assess and evaluate. In contrast, novelty, relatedness, and future growth potential are much harder to measure and hence to consider. An applicant's track record is likely to receive more weight in the granting decision than ideas’ novelty or their implications for regional diversification. While the EU's Smart Specialization strategy tries to give more weight to these elements, according to our results, it has not (yet) influenced the design of Germany's project-based R&D subsidization scheme. This might be due to a generally risk-averse innovation system in Germany (see discussion in Dohse (2000)). However, it might also be the case that policy misses empirical measures that can be used in this context. Developing tools and measures of novelty, growth potential and relatedness as well as making these accessible to policy therefore seems to be a crucial next step.

The study shows that relatedness plays an important role in the allocation of R&D subsidies. That is, technologies that are related to regions' technology portfolio have higher likelihoods of receiving public support. This seems to be in line with the recent literature on related variety (Frenken et al., 2007; Neffke et al., 2011) and with the Smart Specialization approach on a first sight. However, the results further indicate that while subsidies are awarded to related fields, these fields are not new to regions' technological portfolio. Hence, the subsidization does not support related diversification but promotes the solidification of existing technological structures and degrees of relatedness.

A crucial question (which is rarely discussed) in this respect is if policy should actually try to facilitate diversification into technologies related to regions' technology portfolios. The regional branching mechanism suggests that such technologies are most likely to emerge in these regions anyway. Put differently, is related diversification really troubled by market failures, which justify policy intervention? Regional branching implies that regional diversification is a path-dependent process, which might lead to a thinning out of regional knowledge diversity. This in turn increases the risks of regional lock-ins.

From a market-failure perspective, it might therefore be more useful to stimulate diversification into unrelated technologies, as these are most unlikely to take place. Unrelated technologies are at large technological distances to the regional portfolio. By supporting unrelated diversification policy will increase regional knowledge diversity. Through a portfolio effect, diversity will make regions more resilient with respect to external shocks, which some authors argue should be one of innovation policy's main targets (Martin, 2012). In addition, regional knowledge diversity lays the ground for unexpected and uncommon knowledge recombination, which frequently form the basis for breakthrough invention (Uzzi et al., 2013; Kim et al., 2016).

While it is not the aim of the present paper to solve this debate, we believe that in contrast to specialization, related diversification provides sufficient variety to avoid regional lock-in scenarios. Usually, for each region multiple opportunities for related diversification exist. Accordingly, there is diversity in related diversification opportunities. It is this diversity which makes lock-ins and negative long-term effects unlikely when supporting underdeveloped but related technologies. Accordingly, pursuing a policy of supporting related diversification represents smart policy behavior. It exploits promising local opportunities while simultaneously minimizing the risk of failures. In the rare cases of regions offering just one related diversification possibility, it might however be worthwhile to promote unrelated diversification in order to lay the foundation for more related diversification opportunities in the future.

7 Concluding remarks

R&D subsidies play a crucial role for innovation policy. Ideally, they support the development of ideas, which lay the foundation for future economic growth. Despite a flourishing literature evaluating R&D subsidies, it is still unclear how R&D subsidies are (and should be) allocated and under what conditions what type of effects emerge from their provision.

In a first attempt, the paper discussed and empirically analyzed R&D subsidies from the perspective of Evolutionary Economic Geography. We evaluated the allocation and effects of R&D subsidies considering the relation between subsidized technologies and their regional context in terms of relatedness. In contrast to most existing studies, we were particularly interested in R&D subsidies' effects on regional diversification. Our results clearly indicate that R&D policy in Germany does not promote and affect regional technological diversification. German R&D subsidization primarily focuses on well-established technologies.

However, our empirical research design has some limitations that need to be pointed out and considered when interpreting our findings. Most importantly, due to difficulties in matching R&D subsidies to patent data, our analysis covers only a small sample of the technological and subsidization landscape. Moreover, by using patent information, our observations capture just a fraction of all invention activities. Moreover, we exclusively considered

R&D subsidies by the German federal government. Other support measures such as the financing of basic research, investments in human capital and funding programs by other administrative bodies are ignored.

These drawbacks and the results of our study clearly call for more research in the future. R&D policy still misses the right tools to identify promising but underdeveloped technologies and for evaluating the spatial context in which they evolve. We believe that our paper makes a step in that direction by showing that regional branching helps in understanding the economic transformation of regions and providing an empirical set-up for evaluating the role of a specific policy tool (R&D subsidies) in this context.

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