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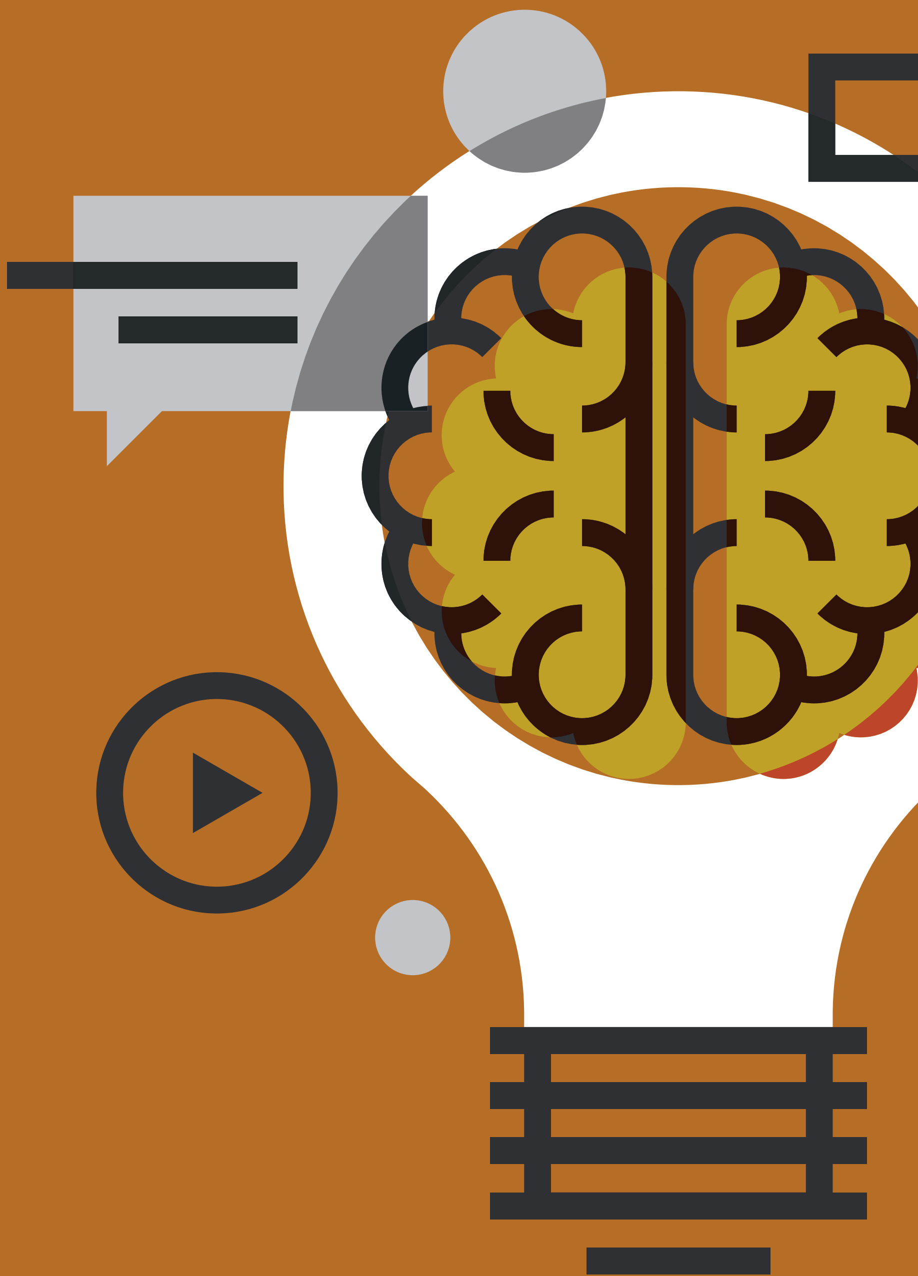

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R&D subsidies and diversification in new industries and technologies in Swedish regions: a study of VINNOVA programs 2010-2012

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Summary

Every region is subject to structural change (Pasinetti 1981; Saviotti and Pyka 2004). Economic activities in regions come and go. Every regional economy is subject to losses of existing activities that come in different forms: closure of start-ups, bankruptcy of companies, the collapse of whole sectors, the decline and substitution of technologies, the transition away from a fossil fuel-based economy, et cetera. Within this context of decline, innovation and renewal take place at the same time: new firms are founded, new industries come into existence, new technologies are being developed, and a green economy is on the rise. To secure long-term economic development, these processes of entry and growth need to exceed processes of stagnation, decline and exit in regions. In other words, regions need to develop new economic activities, to compensate for the inevitable decline and loss of their existing activities.

This makes diversification a key societal challenge for any regional economy. It requires understanding of how regions develop new activities, and to what extent public policy can intervene to enhance this diversification process. In recent years, an expanding body of research has demonstrated that regions tend to develop new activities (technologies, industries) closely related to existing activities in a region (Boschma 2017; Hidalgo et al. 2018). Local activities provide relevant capabilities (like knowledge and skills) that new activities can build on and exploit. But it also implies that regions cannot diversify in any direction: local capabilities also set limits to the diversification process. A region that lacks capabilities in cybersecurity, for instance, is unlikely to excel in developing advanced blockchain-based solutions.

However, there is yet little understanding of how public policy intervention may affect regional diversification, on top of the importance of local capabilities. Public provision of R&D grants may have such an effect, the more so because R&D grants can be targeted to specific technologies and industries a region would like to develop more fully. This project takes up this question: is there any evidence that R&D grants might induce regional diversification?

We examined whether VINNOVA research and innovation programs implemented in the period 2010-2012 correlate with the development of new industries and technologies in Swedish regions in the years after. We analyzed whether Swedish regions that receive more R&D funding in a specific industry or technology are also more likely to diversify in this

industry and technology. We also examined whether this relationship is stronger for collaborative R&D projects, as compared to non-collaborative R&D projects. Finally, we investigated whether R&D grants may still be able to stimulate regional diversification when relevant local capabilities are missing in the region. To what extent can R&D grants compensate for missing local capabilities and contribute to (unrelated) diversification in a region? Or are local capabilities more likely to strengthen the relationship between R&D grants and regional diversification, and thus enhance the possible effect of R&D grants in the region?

We calculated an entry model that estimates the probability that (1) a region specializes or not in a new industry during the period 2014-2016; (2) a region specializes or not in a new technology during the period 2014-2018. Observations include all industries (technologies) in which the region was not specialized in during the period 2011-2013 (2009-2013 for technologies). Industry data is taken from a comprehensive dataset of all Swedish plants provided by Statistics Sweden, while technology data is derived from the OECD-REGPAT patent dataset. In the entry model, we estimate whether local capabilities and R&D grants correlate with the entry of new industries and new technologies in Swedish regions.

To capture the possible effect of local capabilities, we first had to determine the degree of relatedness between industries and between technologies. Activities are considered related when they share similar capabilities. For instance, motor cycles and cars are related because they rely on similar knowledge and engineering skills, while agriculture and nuclear energy are considered unrelated, as they have nothing in common in terms of capabilities. For industries, we determined the degree of skill-relatedness between industries, based on labor mobility flows across industries in Sweden. For technologies, we determined the degree of relatedness between technologies, based on the frequency of combinations of technology classes occurring on a patent document in Europe. We used this information on relatedness to construct an indicator that captures how related a potential new industry (technology) is to existing industries (technologies) in a region. We expect a positive relationship between entry and local capablities: the more related a potential new activity is to existing activities in a region, the lower the costs to develop this new activity, the higher its entry probability.

To estimate the possible effect of R&D grants, we analyzed all Vinnova innovation subsidies paid out during the years 2010-2012. It includes a variety of R&D programs. Promoting R&D collaboration is a key goal in many of the programs. A total amount of 13.5 billion SEK was invested in the R&D projects, of which 6.4 billion SEK came from Vinnova, and 7.1 billion SEK from co-financing by participants. The Vinnova data allowed us to link the subsidies to regions, industry codes (5-digit) and technology classes (4-digit).

The main findings of the study can be summarized as follows.

First of all, we find strong evidence that local pre-existing capabilities condition the entry of new industries and new technologies in Swedish regions. This confirms findings of other studies that regions tend to diversify in new activities strongly related to existing activities in regions. If a region lacks relevant capabilities (like knowledge and skills), the more unrelated a potential new activity is to existing activities in a region, the higher the costs to develop this new activity, and the lower the probability that such a new activity will emerge and grow in that region.

Second, we show that regions receiving R&D grants in VINNOVA programs in a specific industry or technology are more likely to diversify into this industry and technology. This is especially true for technological diversification. We also made a distinction between R&D grants to firms and R&D grants to non-firms, most of them universities. The analyses showed that R&D grants to non-firms seem to matter for technological diversification, but not for industrial diversification. This does not come as a surprise, as R&D grants to universities are more likely to increase the level of patenting rather than the level of employment in industries in regions, especially in the short-run.

Third, regions with more collaborative R&D grants in VINNOVA programs are more likely to diversify into new industries and technologies. This finding of a positive correlation between collaborative R&D grants and regional diversification is in line with literature stressing the importance of research collaboration for innovation. In contrast, we did not find a general tendency of regions with more non-collaborative grants to diversify into new industries. This suggests that non-collaborative R&D funding is not pushing the development of new industries in the region, at least not in the short run. However, we found a positive relationship between non-collaborative grants and the development of new technologies in Swedish regions.

Fourth, we found that the relationship between R&D grants and regional diversification is strongest when relevant local capabilities are present in the region. So, we did not find evidence of a relationship between R&D grants and regional diversification when relevant local capabilities are missing. Local capabilities tend to enhance the possible effect of R&D grants on successful diversification in a region. Even when there was no evidence of a direct relationship between non-collaborative grants and industrial diversification in regions, we still found a positive coefficient of their interaction term. A plausible interpretation is that non-collaborative grants could still favour the development of new industries in Swedish regions, but only when relevant local capabilities are present.

If we compare the results for industrial and technological diversification, we observe that R&D grants are more likely to be correlated with technological diversification, and less so with industrial diversification in regions. This is not unexpected: R&D grants are more likely to generate new knowledge that lead to new patents and new technologies, but not necessarily to employment growth and the development of new industries in a region, at least in the short run.

A key objective of the study was to analyze different VINNOVA research and innovation programs at the same time. We also looked more in detail at two of the largest programs, the Vehicles program and the VINN Excellence Centre program. The Vehicles program is directed at the automotive industry, while the VINN Excellence Centre program supports fundamental, industry-related research in research centres like universities. The findings suggest that R&D grants in the VINN Excellence Centre program can be associated with the entry of both new technologies and new industries in Swedish regions. R&D grants in the Vehicle program seem to support the entry of new technologies, rather than the entry of new industries in regions.

We see this study as a first step towards assessing the full impact of R&D grants on diversification of the Swedish economy. Our study aimed to explore the relationship (or correlation) between R&D grants and technological and industrial diversification in Swedish regions, rather than demonstrating a causal link between the two. One also has to remind that we examined only R&D programs initiated and run by VINNOVA, which take up a fraction of all R&D grants provided by the Swedish national government. Moreover, we have not accounted for the impact of international R&D grants (like the participation of Swedish regions in the EU Framework Programs) either. Including those R&D programs would be a next step to take a full account of the effects of R&D grants on regional diversification.

Despite all these remarks of caution, we still think we can draw some policy implications. First, it seems that R&D grants may be a useful tool to make Swedish regions diversify into new activities. It may be used as a policy instrument (alongside other policy instruments) to induce the development of new activities that Swedish regions aim to target in their regional development plans. The advantage of R&D grants as a policy tool is that they can be targeted to specific technologies and industries that public policy wants to promote, like Smart Specialization policy in the European Union (Balland et al. 2019a). Second, the analyses provide some evidence that collaborative R&D grants matter especially for regional diversification. The advantage of using collaborative R&D grants as a policy tool is that it can promote interaction across different activities that is widely deemed crucial for innovation and diversification in regions. This requires a careful selection of partners in R&D projects that are publicly funded. Other studies have shown that it is crucial for innovation to bring in the right partners in collaborative research networks in terms of (related) variety of competences (Fleming et al. 2007; Gilsing et al. 2007; Cassi and Plunket 2015).

Third, the results suggest that R&D grants have more of an impact on the development of new technologies rather than new industries in regions, at least in the short term. This implies that, on top of R&D grants, other policy actions (like new regulations, or stimulating the local supply of venture capital) might be needed to ensure that R&D grants will not only lead to new knowledge and technologies, but that these are also transformed into economic development and the creation of new firms and new economic sectors.

Finally, a key finding of the study was that the possible effects of public support of R&D are not independent of capabilities in a region. This may imply that public research and innovation programs need to account for local capabilities. However, there are divergent views on that. On the one hand, R&D programs might make more sense when they target new activities in which a Swedish region has high potential due to the presence of relevant capabilities. R&D policy is more likely to be effective when it avoids building new activities in regions from scratch, as this study also tends to suggest. On the other hand, one could argue that R&D grants should also focus on radical change (i.e. less related diversification). This is because markets will not take up easily R&D projects that are very risky, and regions might become locked-in in old and mature specializations at some point of time (Crespo et al. 2014).

1. Introduction

To secure long-term economic development, regions have to develop new economic activities, in order to compensate for the inevitable stagnation, decline, and disappearance of existing economic activities (Boschma 2018). What is common knowledge is that some regions are more successful in doing so than others, and therefore prosper more in economic terms.

For illustrative purposes, we show in Figures 1-4 two contrasting regional cases of structural change in Sweden: the Linköping-Norrköping region and the Skövde – Skara region. In Figures 1 and 3, we show on the Y-axis the intensity of patent activity in five broad technological domains in each region, in terms of their share in total patenting activity in the region. The X-axis shows how these shares change over time, comparing five periods (1994-1998, 1999-2003, 2004-2008, 2009-2013, 2014-2018). Figures 2 and 4 show the treemaps of the technological portfolio of the two regions for the most recent period 2014-2018. The Linköping-Norrköping region shows a strong ability to increase its share in modern technologies in electrical engineering during the period 1994-2018. In contrast, the Skövde – Skara region seems to get stuck more and more in mature technologies in mechanical engineering.

Figure 1. Structural change in Linköping-Norrköping region 1994-2018

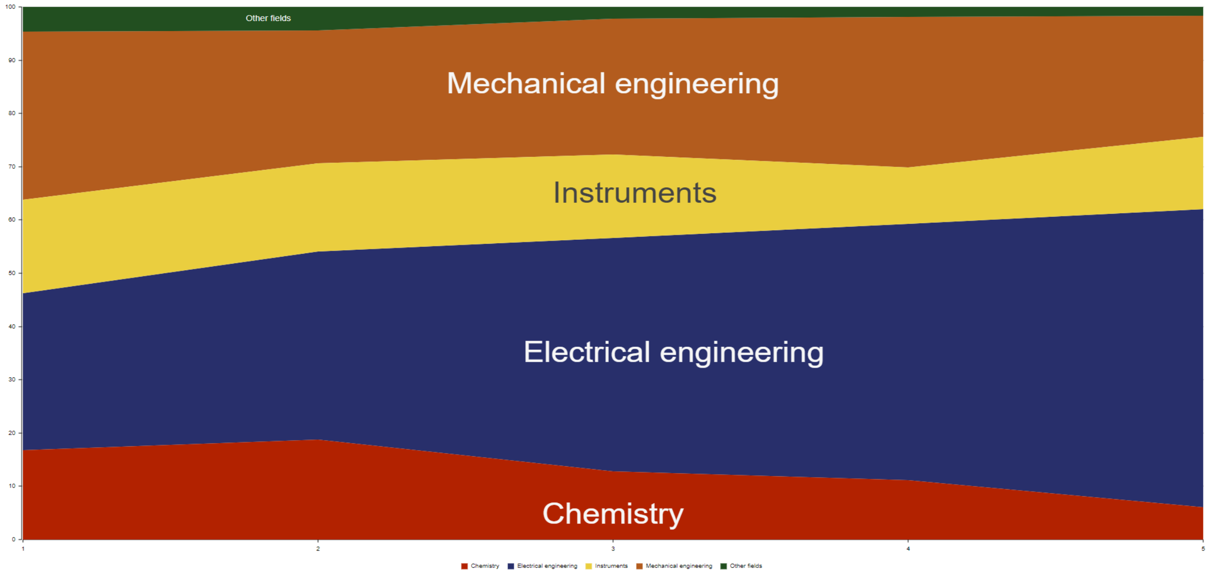


Figure 2. Current technological portfolio of the Linköping-Norrköping region 2014-2018

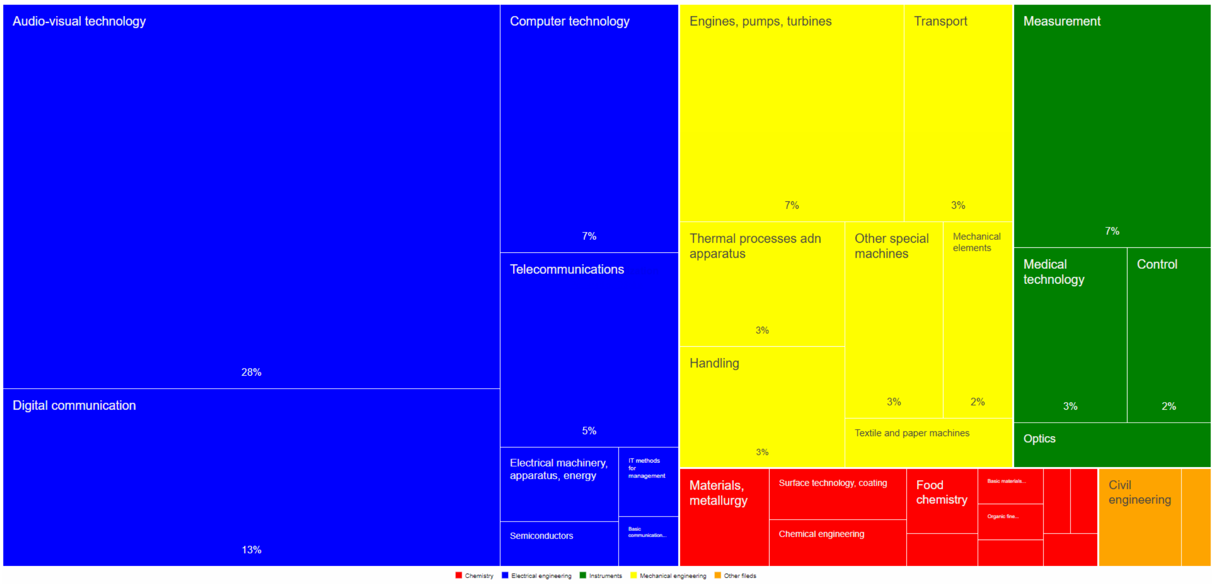


Figure 3. Structural change in Skövde – Skara region 1994-2018

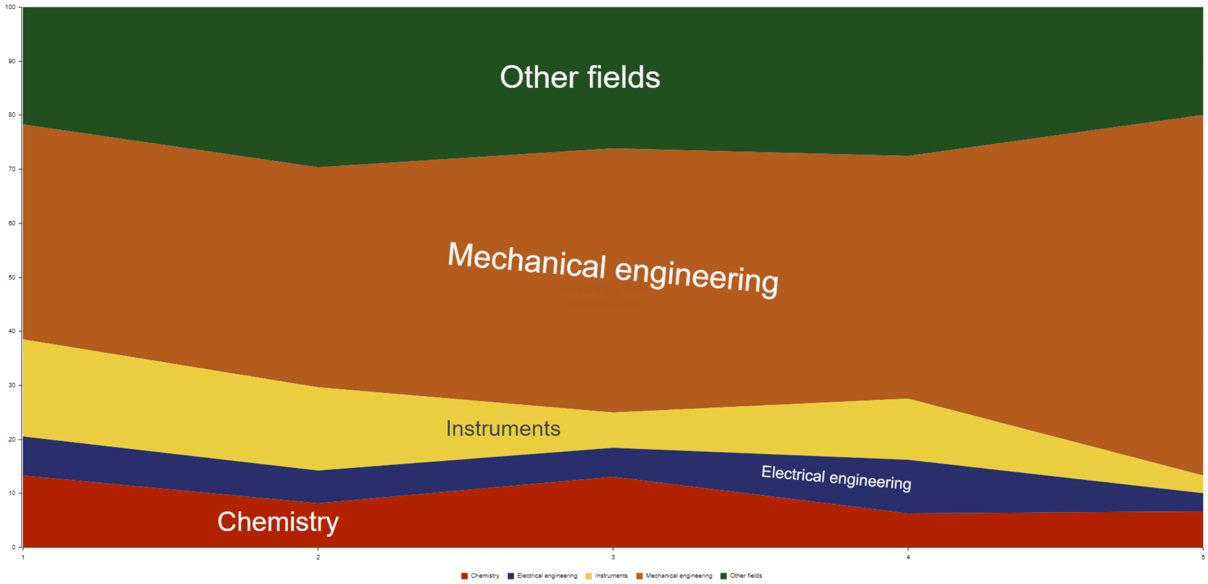
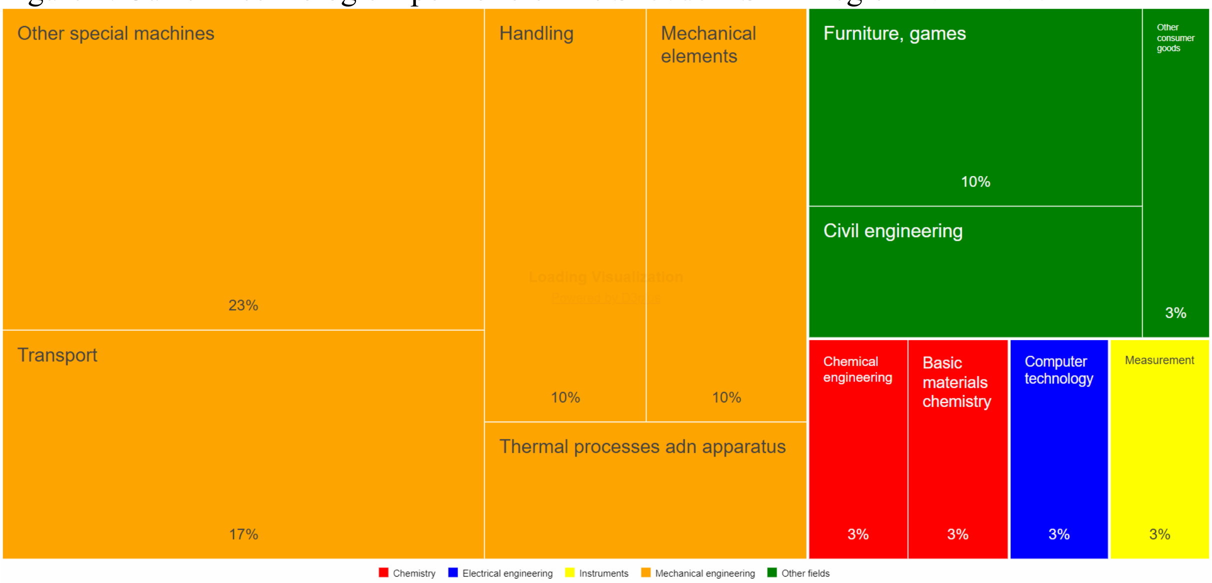


Figure 4. Current technological portfolio of the Skövde – Skara region 2014-2018



To understand these processes of structural change in regions, we need to understand how regions develop new economic activities over time, and to what extent public policy can make an impact in this respect. The key question is: can a successful diversification process in regions be stimulated and encouraged by public policy intervention? There is widespread belief that enhancing collaboration and interaction between universities, industries, and government may foster innovation and economic development (Etzkowitz and Leydesdorff 2000). The EU is funding thousands of collaborative research and innovation projects through its Framework Programs (European Commission 2018; Balland et al. 2019b). Many countries have developed programs promoting collaboration, especially between universities and firms, to ensure that publicly funded research benefits the economy as a whole. Sweden is no exception (OECD 2016). Collaborative R&D projects are a big part of Swedish innovation policy (Growth Analysis 2019). Studies have assessed the impact of subsidies for R&D collaboration on the performance of firms (Halvarsson et al. 2018) and regions (Hoekman et al. 2013). However, there are few studies to date that look at their impact on regional diversification, and whether collaborative R&D grants can contribute to inducing structural change in regional economies (Uhlbach et al. 2017; Broekel and Mewes 2017). This project will make a first step in tackling this question, looking at industry and patent data at the regional scale.

We apply a relatedness framework to analyze how Swedish regions diversify over time (Neffke et al. 2011; Boschma 2017; Balland et al. 2019a). This framework builds on the so-called principle of relatedness (Hidalgo et al. 2018) that claims that emergence of new economic activities (technologies, industries) is closely related to existing activities in a region. That is, new activities tend to build on local capabilities (like knowledge and skills) that provide opportunities but also set limits to a successful diversification process. This project focuses on the possible impact of (collaborative and non-collaborative) R&D grants on technological and industrial diversification in regions, while controlling for the impact of local capabilities. Moreover, it examines whether these R&D grants either strengthen or weaken the relationship between relatedness and regional diversification. The former would reveal less radical change in regional economies, while the latter would imply more radical change.

The main research question is: is there any evidence that R&D grants induce the development of new technologies and new industries in Swedish regions? We investigate whether VINNOVA research and innovation programs implemented in the period 2010-2012 may have had an impact on diversification in Swedish regions in the years after. We analyze whether Swedish regions that receive more funding in a specific industry and technology are also more likely to diversify in this industry and technology. We make a distinction between collaborative R&D projects and non-collaborative R&D projects. We also analyze if R&D grants are associated with more or less radical change in regions (i.e., less or more related diversification). The outcome of such analysis has implications for research and innovation policy in Sweden.

The report is structured as follows. Section 2 gives a short literature review. Section 3 presents the data and methods. Section 4 presents the main outcomes. Section 5 concludes.

2. R&D subsidies and regional diversification

Knowledge and innovation are key to the well-being of any economy. Firms not only produce new knowledge through R&D investments and other forms of knowledge creation, they also try to get access to external knowledge (Antonelli and Colombelli 2015). Knowledge production has become a collective activity in which firms and other organizations interact and recombine knowledge. This is confirmed by an increasing tendency of collaborative research over time, both in teams within firms (Wuchty et al. 2007), and in projects across firms and other organizations (van der Wouden and Rigby 2017).

Public policy has played a role in this respect. For many decades and in many industrialized countries, the state has provided R&D subsidies and has tried to stimulate R&D collaboration. Collaborative research is promoted by public policy because, among other things, it would facilitate knowledge spillovers and cross-fertilization across organizations, such as firms and universities (Katz and Martin 1997; Etzkowitz and Leydesdorff 2000). Countries like Germany (Schwartz et al. 2012) and Sweden (OECD 2016) have been active in promoting collaboration, especially between universities and firms. The EU is also funding collaborative research and innovation projects through its Framework Programs (Maggioni et al. 2014; European Commission 2018 Balland et al. 2019b).

There is a lot of research on the effects of R&D subsidies on firm performance (Zuñiga-Vicente et al. 2014; Czarnitzki and Hussinger 2018). The same applies to studies on R&D collaboration and the performance of firms. There is substantial evidence of a positive effect of public support of collaboration on R&D and knowledge creation in firms (Czarnitzki et al. 2007; Schwartz et al. 2012; Scandura 2016; Czarnitzki and Hussinger 2018). Matt et al. (2012) found that EU-funded R&D partnerships tended to be more explorative and research-based, as compared to partnerships without EU support. Moreover, studies found empirical support for a positive effect of research collaboration on the innovative capacity of firms (Aschhoff and Schmidt 2008; Lööf and Broström 2008) and their productivity (Arvanitis et al. 2008). Halvarsson et al. (2018) looked at the impact of collaboration on the performance of small firms that participated in 65 publicly funded innovation aid programs in Sweden. This study found a positive effect on sales growth but no effect on employment growth.

Studies have also investigated the impact of (inter-regional) R&D collaboration on the performance of regions. Hoekman et al. (2013) found a slight positive effect of EU-FP funding in lagging regions in the EU. Di Cagno et al. (2016) reported a positive effect of participation in EU Framework Programs on knowledge creation in European regions. De Noni et al (2018) identified a positive effect of collaboration with knowledge-intensive regions on the innovative performance of lagging European regions. Broekel (2015) found that German regions with low innovation capacities benefit from intra-regional collaboration across firms and subsidized links with public research institutes outside their own region. Barzotto et al. (2019) showed that regions with weaker knowledge capabilities, such as peripheral regions, benefit more from inter-regional knowledge collaboration. Miguelez and Moreno (2018) found that inter-regional knowledge linkages have a higher impact on innovation in European regions when the similarity between these knowledge flows and the local knowledge base is higher.

A key question remains whether R&D grants can induce structural change in regional economies. Few studies have assessed the impact of public support of R&D collaboration on regional diversification. Uhlbach et al. (2017) showed that Framework Program (FP) participations by EU regions have a positive though relatively small effect on the development of new technologies in regions during the period 1999-2010. Broekel and Mewes (2017) found that subsidized R&D projects promote technological diversification in 141 German regions from 1991 to 2010. This effect appeared to be stronger for subsidized joint R&D projects, compared to subsidized R&D projects conducted by a single organization.

What is known is that regions tend to develop new activities (technologies, industries, occupations) that are closely related to existing activities in a region (Boschma 2017; Hidalgo et al. 2018). Local activities can provide relevant capabilities (like knowledge and skills) that new activities can exploit. In this respect, they provide opportunities but also set limits to a successful diversification process in regions. Many studies have confirmed the importance of related diversification in regions (e.g. Neffke et al. 2011; Kogler et al. 2013; Rigby 2015).

But can (collaborative and non-collaborative) R&D grants induce the development of new industries or technologies in a regional economy, on top of local capabilities? And when important, is R&D funding more likely to induce related diversification (creating new activities that are related to existing activities in a region) or more unrelated diversification (creating new activities that are unrelated to existing activities in a region). There are no studies yet that address these questions in a systematic manner. Broekel and Mewes (2017) concluded that R&D subsidies in Germany tend to reinforce the path-dependent nature of regional diversification, as they are allocated to technologies that are strongly related to existing technologies in the region. Uhlbach et al. (2017) showed that a lack of relevant capabilities may be compensated to some extent by Framework Program participations to develop new technological specializations in European regions. This study suggests that R&D subsidies (through collaborative FP programs) have impact on the development of new technological specializations in regions when the level of relatedness with local capabilities is neither too low nor too high. In other words, R&D subsidies cannot create cathedrals in the desert in regions, nor will they have much impact when all relevant capabilities are already present in the region.

3. Data and methods

This project focuses on the possible impact of public support of R&D projects on technological and industrial diversification in regions, while controlling for the impact of local capabilities. This study is not interested in the question whether public R&D grants tend to reinforce existing specializations in regions. Instead, we focus on their possible effect on the emergence of new specializations in technologies and industries in regions, as diversification is crucial for their long-term development. The main research question is: do collaborative and non-collaborative R&D grants induce the development of new industries or technologies in a regional economy, on top of local capabilities? We also analyze if R&D public funding induces more related diversification (i.e. more related to existing industries or technologies in a region) or less related diversification (i.e. related to a lesser extent to existing industries or technologies in a region).

To analyze regional diversification, we look both at diversification into new technologies and new industries. New technologies take up new knowledge creation in a region, which, however, might not necessarily lead to innovation and the development of new economic activities. For that purpose, we also look at the emergence of new industries in regions.

Industrial diversification of regions

First, we discuss the data and variables to investigate industrial diversification. We combined two datasets provided by the Swedish Agency for Growth Policy Analysis: (1) a project-participant dataset on VINNOVA innovation subsidies during the period 2010-2012, and (2) a dataset with the full population of Swedish plants (key variables include number of employees, plant municipality, industry codes, value-added) from Statistics Sweden. This allowed us to estimate the funding received by a given municipality in a given industry (2 and 5 digits).

Based on these data sources, we are able to derive a dataset that has one observation per industry, year and region for the years 2011-2016. All monetary variables are denoted in thousand SEK. Industries are defined by the NACE Revision 2 classification, and the analyses are done at the 2-digit level (total of 82 industries, or 'divisions') and the 5-digit level[1] (total of 786 industries or 'classes').

The size of the industry in the industry-region-year is determined as the average number of employees during the year. This variable is rounded of, so if a plant employed less than one full-time worker equivalent during a year, this variable is equal to zero. This information is taken from the main Business Register, known as FEK. FEK includes yearly information on the organization/firm level as well as on the plant/establishment level. Our dataset is based on plant-level data, where each plant has a NACE code and linked to a municipality.

We analyze 60 metropolitan regions or labor market areas. These are defined by the labor market classification known as FA15 (Functional Analysis regions, 2015 revision). FA15 assigns municipalities to labor market regions based on commuting patterns.

The dependent variable is the entry (or not) of a new industry (either at the 2 or 5 digit level) in a region. Our observations consist of industries in which a region was not specialized during the period 2011-2013. So we leave out industry-region observations that involve an industry in which a region was already specialized in that period. We employ an *entry model* that estimates the probability that a region specializes in a new industry in the period 2014-2016. Following other studies (e.g. Rigby 2015. Balland et al. 2019a), we calculate Relative Industrial Advantage (RIA) to assess whether a region becomes specialized or not in an industry that is new to the region. RIA is a binary variable that assumes the value 1 when a region possesses a greater share of employment in industry i than Sweden as a whole, and assumes value 0 otherwise. A region r has RIA in industry i (r = 1,..., n; i = 1, …, k) such that〖RIA〗_(r,i)^t=1 if:

$$\frac{\boldsymbol{employment^t_{r,i}} / \sum_i \boldsymbol{employment^t_{r,i}}}{\sum_r \boldsymbol{employment^t_{r,i}} / \sum_r \sum_i \boldsymbol{employment^t_{r,i}}} > \mathbf{1}$$

The variable $Entry_{i,r,t}$ = 1 if an industry i that did not belong to the portfolio of the region r at time t-1 (2011-2013) enters the region in time t (2014-2016), otherwise it gets a score of 0. This implies that an entry is identified when the industry in a region had an RIA<1 at t-1, and an RIA>1 at time t. We did some robustness checks with other values of RIA. However, our findings remained the same. Since we are interested in diversification and structural change in regions, we take entry as dependent variable, not changes in the RIA more in general.

We have three categories of independent variables. Appendix 1 provides the full list of variables. Appendix 2 presents some descriptives of all variables plus a correlation matrix.

[1] We use 4-digit industries when these are not further decomposed.

The first category of independent variables concerns local capabilities, to assess whether relatedness has a positive effect on the entry of new industries in a region. Following other studies, we constructed a so-called Relatedness Density variable. This requires two steps.

First, we determined the degree of relatedness between each pair of industries following the skill-relatedness approach (Neffke and Henning 2013). The metric is computed in two steps. First, we count the number of employees that switch jobs from industry i to industry j in period t. This gives us an asymmetric matrix, as more individuals might leave a job in industry i and find a job in industry j, than the other way around. To account for different industry size, we normalize this count in a second step using the cosine index (Van Eck and Waltman 2009) implemented in the EconGeo R package (Balland 2017). This allows us to draw a so-called 'industry space' for Sweden which is visualized as a network in Figure 5. Each node represents one 2-digit industry, and if there is a link between 2 industries, it means they are skill-related above a certain threshold. As one can observe, some industries are skill-related to many other industries (those are the ones more centrally positioned in this network), while other industries are skill-related to only one or a few sectors (the ones located at the periphery of the network). The colours of the nodes refer to the seven 1-digit industries.

Figure 5. Industry Space

Second, we use this relatedness information to calculate a Relatedness Density measure, following Hidalgo et al. (2007) and Balland et al. (2019a), to assess the effect of regional capabilities on regional diversification. The Relatedness Density indicates how close a potential new industry is to existing industries in a given region. The Relatedness Density around an industry i in region r at time t is derived from the sum of relatedness of industry i to all other industries j in which the region has a Relative Industrial Advantage (RIA), divided by the sum of relatedness of industry i to all other industries j in the reference region (Sweden) at time t:

$$\text{RELATEDNESS\_DENSITY}_{i,r,t} = \frac{\sum_{j \in r, j \neq i} \phi_{ij}}{\sum_{j \neq i} \phi_{ij}} * 100$$

The second group of independent variables concern the subsidy variables. To capture the effects of R&D grants in Sweden, we analyzed subsidies allocated by Vinnova in the years 2010-2012. The programs have in common that they are all supposed to promote innovation in one way or another, but there is great variety when it comes to program design and focus. Promoting R&D collaboration between different organizations is a key goal for many of the programs, but not for all. The analysis focuses on subsidies to innovation projects where at least one firm participated (about 55 % of the subsidies), thus allowing us to tie subsidies to industries.

The subsidy data covers all Vinnova innovation subsidies paid out during the years 2010-2012. (Halvarsson et al. 2018). A range of actors, like private companies (2,400), colleges and universities (52), research institutes (37), miscellaneous public actors (348), and others (288) participated in about 4,000 projects. Universities and colleges received 45 percent of the funding, followed by private companies (25 percent), research institutes (13 percent), miscellaneous public actors (11 percent) and others (6 percent) (Halvarsson et al. 2018). For most programs, Vinnova set requirements that the actors receiving funds should co-finance the projects for which they received support. In total, 13.5 billion SEK was invested in the funded R&D projects, 6.4 billion SEK from Vinnova and 7.1 billion SEK through co-financing from participants. This amount of 13.5 billion SEK takes up about 4 percent of all R&D investments in Sweden in the period 2010-2012. The 6.4 billion SEK that VINNOVA allocated to R&D subsidies during that period amounted to 6–7 percent of the government's total R&D budget. The ten largest programs that accounted for 49 percent of total grants are shown in Table 1.

Table 1. The ten largest principal programs 2010–12

	Principal program	Amount of aid	Co-funding	#projects	#participants per project
1	FFI – Strategic vehicle research and innov.	923	846	258	5.0
2	Research&Grow	377	429	544	1.1
3	VINN Excellence Centre	336	856	38	9.1
4	EUREKA and Eurostars	261	656	341	1.5
5	VINNVÄXT	239	267	48	3.5
6	Technical aviation research program	212	217	97	2.2
7	Innovations for future health	205	158	42	1.7
8	Challenge-driven innovation	199	133	168	4.8
9	Incubators	192	5	10	1.5
10	VINNMER	180	95	190	1.1

Note: Amount dispensed during 2010–12, in millions of kronor

Source: Halvarsson et al. (2018). p. 20

The Vinnova data in most cases includes plant ID, thus allowing us to connect the subsidies to a region and a NACE code. The dataset includes 91 % of the total Vinnova subsidies and 97 % of the subsidies granted to firms. NACE code and municipality for so-called ‘non-firms’ were obtained from the RAMS plant registry dataset which includes the public sector. We used a concordance table to connect NACE codes and CPCs[2].

The Vinnova data is broken down by project, actor and year, allowing us to see which organizations collaborate with each other in R&D consortia. We observe how much each organization receives in subsidies in each project-year, how much they contributed in co-financing to the project, which program the project was part of, among other variables. In the final dataset, subsidies and co-financing are aggregated by region-industry-year. The main estimations will put together firms that received a subsidy with co-funding (so-called co-funding firms) and firms that received a subsidy with no co-funding (so-called subsidized

[2] See link: https://circabc.europa.eu/sd/a/d1475596-1568-408a-9191-426629047e31/2014-10-16-Final%20IPC_NACE2_2014.pdf

firms). We will carry out the same estimations for each of these two types of firms separately that will be reported in Appendices 3 and 4.

We constructed three subsidy variables focused on firms. For co-funding firms and subsidized firms taken together, we constructed three subsidy variables: (1) tot.rd (log): total amount of direct R&D subsidies to firms plus co-financing by firms, in thousands of SEK; (2) tot.rd.collab (log): total amount of direct R&D subsidies to firms in collaborative projects plus co-financing to collaborative projects by firms, in thousands of SEK; (3) tot.rd.non.collab (log): total amount of direct R&D subsidies to firms in non-collaborative projects plus co-financing to non-collaborative projects by firms, in thousands of SEK.

We also include three interaction variables, to examine whether the effect of the three subsidy variables is strengthened or weakened by relatedness. A positive effect of an interaction variable would indicate that the higher the relatedness in a region, the higher the effect of R&D subsidies, suggesting a complementarity relationship. Instead, a negative effect would suggest that the higher the relatedness, the lower the effect of R&D subsidies, and vice versa, implying a substitution effect. We calculate three interaction variables: (1) the variable RD*tot.rd which is the interaction term of Relatedness Density (RD) with total R&D subsidies and co-financing by firms; (2) the variable RD*tot.rd.collab which is the interaction term of RD with total of R&D collaborative projects; (3) the variable RD*tot.rd.non.collab which is the interaction term of RD with total of R&D non-collaborative projects.

We also constructed four subsidy variables focused on so-called non-firms. Since we want to attribute a subsidy to a nace code, we do not estimate a variable that accounts only for direct R&D subsidies to non-firms. We use the nace codes of firms in the project. So if Lund University collaborates with Telecom companies, we consider that the Telecom sector in Lund receives the subsidy. We defined 4 variables: (1) subsidy_nonfirms_distrib (log): R&D subsidies to non-firms in the region, distributed based on firms' co-funding, in thousands of SEK; (2) subsidy_nonfirms_distrib_coord (log): same, but only for subsidies to project coordinator leader, in thousands of SEK; (3) subsidy_nonfirms_indirect (log): R&D subsidies to non-firms, assigned to firms in project, in thousands of SEK; (4) cofin_nonfirms (log): co-financing contributed by non-firms, in thousands of SEK.

Table 2. Amounts of all R&D subsidies and co-financing, 2010–12

Subsidy variable	Amount, million SEK, 2010-2012
Total.rd	4 829
Total.rd.collab	3 219
Total.rd.non.collab	1 610
Cofin_firms	3 261
Cofin_firms_collab	2 464
Cofin_firms_noncollab	797
Subsidy_firms	1 568
Subsidy_firms_collab	755
Subsidy_firms_noncollab	813
Subsidy_nonfirms_distrib	1 597
Subsidy_nonfirms_distrib_coord	1 123
Subsidy_nonfirms_indirect	1 779
Cofin_nonfirms	2 747

The third set of independent variables concerns regional control variables. We include three of them: (1) workers_uni: absolute number of workers in higher education (NACE 854) in a region in 2012; (2) grp: gross regional product, SEK millions in 2012; (3) sh.stem: absolute number of workers with STEM college education (>2 years) in a region in 2012. Data on gross regional product comes from Statistics Sweden. Data on number of workers with different levels and types of education in each region comes from LISA individual registry. LISA covers the full population of Swedish adults and includes data on individuals' education and employment.

All specifications are estimated at the region-industry level. We use a linear probability model (LPM) to assess the probability that a region specializes in a new industry (entry) using the following specification:

$$ENTRY_{r,i,t} = \beta_1 RELATEDNESS.DENSITY_{r,i,t-1} + \beta_2 R\&D.Sub_{r,i,t-1}$$
$$+\beta_3 REGIONS_{r,t-1} + \beta_4 RELATEDNESS.DENSITY_{r,i,t-1} * R\&D.Sub_{r,i,t-1} + \varepsilon_{r,i,t}$$

Technological diversification of regions

In order to investigate technological diversification, we combine datasets provided by the Swedish Agency for Growth Policy Analysis for participants-patents (or participants-technology classes) to classify the projects into technological categories. Moreover, we use the OECD-REGPAT dataset (edition 2019) geo-located by inventor addresses for all patents invented by inventors living in Sweden and granted by the European Patent Office up to 2018, classified into around 250,000 CPC classes.

The dataset has one observation per technology, year and region and covers the years 2009-2018. We do the analyses at the 2-digit level (total of 33 technologies, or ‘technology groups’) and the 4-digit level (total of 645 technologies or ‘CPC classes’)[3].

The dependent variable is the entry or not of a new technology (either at the 2 or 4 digit level) in a region. Our observations consist of technologies in which a region was not specialized in during the period 2009-2013. So we drop all technology-region observations that involve a technology in which a region was already specialized in that period. We employ an entry model that estimates the probability that a region specializes in a new technology during the period 2014-2018. Following other studies, we calculate Relative Technological Advantage (RTA) to assess whether a region becomes specialized or not in a technology that is new to the region. RTA is a binary variable that assumes the value 1 when a region possesses a greater share of patents in a technology class i than Europe as a whole, and assumes value 0 otherwise. A region r has RTA in technology i (r = 1,..., n; i = 1, …, k) such that 〚RTA〛_(r,i)^t=1 if:

$$\frac{\boldsymbol{patents_{r,i}^{t}} / \sum_{i} \boldsymbol{patents_{r,i}^{t}}}{\sum_{r} \boldsymbol{patents_{r,i}^{t}} / \sum_{r} \sum_{i} \boldsymbol{patents_{r,i}^{t}}} > \mathbf{1}$$

So the variable $Entry_{i,r,t} = 1$ if a technology i that did not belong to the portfolio of the region r at time t-1 (2009-2013) enters the region in time t (2014-2018), otherwise it gets a score of 0.

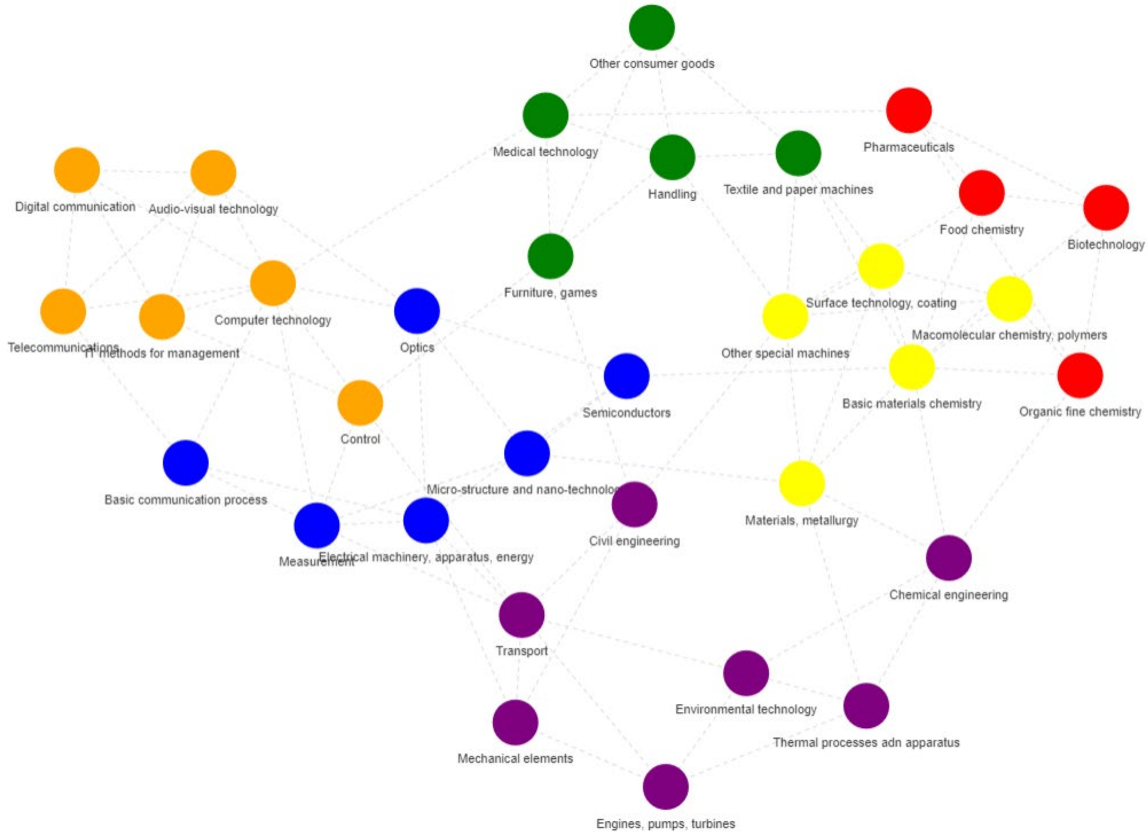
As in the industry entry model, we have three categories of independent variables in the technology entry model.

The first category of independent variables concerns local capabilities, to assess whether relatedness has a positive effect on the entry of new technologies in a region. Once again, we will construct a Relatedness Density variable. This requires two steps.

First, we calculated the degree of relatedness between each pair of technologies (654 CPC technology classes). We make use of co-occurrence analysis of technology classes on a patent document, which measures the frequency of combinations of two technology classes occurring on a patent. Following other studies, we interpret a high frequency as an indicator of technological relatedness. This allows us to draw a ‘technology space’ for Europe that can be visualized as a network in Figure 6, in this case for 2-digit technologies. Each node stands for one 2-digit technology. If there is a link between 2 technologies, then they are related above a certain threshold. Figure 6 shows that some technologies are related to many other technologies (the ones more centrally positioned in the network), while other technologies are related to only one or a few technologies. The colors of the nodes refer to six 1-digit technologies.

[3]We follow the technological classification from Schmoch (2008): https://www.wipo.int/export/sites/www/ipstats/en/statistics/patents/pdf/wipo_ipc_technology.pdf)

Figure 6. Technology Space



Second, we use this relatedness information to calculate a Relatedness Density measure, following other studies (Boschma et al. 2015; Balland et al. 2019a), to assess the effect of local capabilities on regional diversification. For each region r, we calculated the density of technology production in the vicinity of individual technologies i. Following Hidalgo et al. (2007) and Boschma et al. (2015), the density of knowledge production around a given technology i in region r at time t is derived from the sum of relatedness of technology i to all other technologies j in which the region has Relative Technological Advantage (RTA), divided by the sum of relatedness of technology i to all the other technologies j in the reference region (Europe) at time t.

The second and third group of independent variables are the same as in the industry entry model: these concern the subsidy variables and the control variables presented earlier.

In sum, we estimate the following regional entry of a technology model:

$$ENTRY_{r,i,t} = \beta_1 RELATEDNESS.DENSITY_{r,i,t-1} + \beta_2 R\&D.Sub_{r,i,t-1}$$
$$+\beta_3 REGIONS_{r,t-1} + \beta_4 RELATEDNESS.DENSITY_{r,i,t-1} * R\&D.Sub_{r,i,t-1} + \varepsilon_{r,i,t}$$

4. Main findings

Below, we present the entry models for industries at the 5-digit level and technologies at the 4-digit level. Appendix 5 presents the same estimations for industries and technologies at the 2-digit level. We report the main findings in which the firms that received a subsidy with co-funding (co-funding firms) and the firms that received a subsidy with no co-funding (subsidized firms) are taken together. The findings of the same estimations for each of the two types of firms can be found in Appendices 3 and 4. All independent variables have been normalized. This means, for instance, that in Table 3 the first coefficient reads as an additional standard deviation of tot.rd (log) that, in this case, increases the likelihood of entry by about 0.008.

Table 3 shows the findings for industrial diversification for all firms[4]. Relatedness tends to have a positive and significant effect on regional diversification in Sweden, as expected. Moreover, regions that receive R&D grants in a specific industry are more likely to diversify into this industry. The coefficient of collaborative R&D grants is positive and significant, while non-collaborative grants do not seem to matter. The coefficients of the interaction variables are positive and significant, showing that R&D grants tend to have a stronger impact when relatedness is higher in a region.

[4] As a robustness check, we repeated the same estimations while removing every region-industry pair with less than 50 employees. The findings are qualitatively similar.

Table 3. Regional entry of industry (5-digit): role of local capabilities and total R&D grants (all firms)

	Dependent variable:					
	Entry					
	(1)	(2)	(3)	(4)	(5)	(6)
tot.rd (log)	0.008^{***}			0.006^{***}		
	(0.002)			(0.002)		
tot.rd.collab (log)		0.008^{***}			0.007^{***}	
		(0.002)			(0.002)	
tot.rd.non.collab (log)			0.005^{**}			0.003
			(0.002)			(0.002)
workers_uni	-0.0005	-0.0005	-0.001	0.00002	-0.0001	-0.0002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Grp	-0.010^{**}	-0.010^{**}	-0.010^{**}	-0.011^{**}	-0.011^{**}	-0.010^{**}
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
sh.stem	0.122	0.123	0.127	0.109	0.115	0.118
	(0.140)	(0.140)	(0.140)	(0.140)	(0.140)	(0.140)
Related Density (RD)	0.028^{***}	0.028^{***}	0.028^{***}	0.029^{***}	0.029^{***}	0.028^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
RD*tot.rd				0.008^{***}		
				(0.003)		
RD*tot.rd.collab					0.007^{**}	
					(0.003)	
RD*tot.rd.non.collab						0.006^{**}
						(0.003)
Constant	0.063^{***}	0.063^{***}	0.063^{***}	0.064^{***}	0.063^{***}	0.063^{***}
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Observations	20,453	20,453	20,453	20,453	20,453	20,453
R^2	0.011	0.011	0.011	0.011	0.011	0.011
Adjusted R^2	0.011	0.011	0.011	0.011	0.011	0.011
Residual Std. Error	0.244 (df = 20447)	0.244 (df = 20447)	0.244 (df = 20447)	0.243 (df = 20446)	0.243 (df = 20446)	0.244 (df = 20446)
F Statistic	46.038^{***} (df = 5; 20447)	45.778^{***} (df = 5; 20447)	44.722^{***} (df = 5; 20447)	39.595^{***} (df = 6; 20446)	39.121^{***} (df = 6; 20446)	38.083^{***} (df = 6; 20446)
Note:						*p**p***p<0.01

In Appendix 3, we show the same estimations for co-financing firms (Table A3.1) and subsidized firms (Table A3.2). Findings for co-financing firms are almost identical as in Table 3. The same applies to the findings for subsidized firms[5], with one exception. The coefficient of collaborative R&D grants is not significant anymore.

[5] We have done the same analyses measuring RCA based on Value Added (for firms involved in co-financing). The findings are less stable, especially for 2-digit industries.

We have done the same analyses for technological diversification. We only include technology-region pairs with >5 patents during the period. Appendix 4 shows the same estimations for co-financing firms (Table A4.1) and subsidized firms (Table A4.2). Table 4 reports the main findings for 4-digit technologies for all firms. As expected, relatedness tends to have a strong and persistent effect on technological diversification in Swedish regions. Moreover, regions receiving R&D grants in a specific technology are more likely to diversify into this technology. Both collaborative and non-collaborative grants seem to matter. The coefficients of the interaction variables are also positive and significant, showing that R&D grants tend to have a stronger impact when relatedness is higher in a region. Overall, although very similar, the findings on entry of new technologies are stronger than for entry of new industries (Table 3).

Table 4. Regional entry of technology (4-digit): role of local capabilities and total R&D grants (all firms)

	Dependent variable:					
	Entry					
	(1)	(2)	(3)	(4)	(5)	(6)
tot.rd (log)	0.013***			0.020***		
	(0.003)			(0.003)		
tot.rd.collab (log)		0.015***			0.022***	
		(0.003)			(0.003)	
tot.rd.non.collab (log)			0.025***			0.031***
			(0.003)			(0.003)
workers_uni	-0.026**	-0.026**	-0.028***	-0.027***	-0.026**	-0.029***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Grp	-0.071***	-0.071***	-0.072***	-0.072***	-0.073***	-0.074***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
sh.stem	-5.466***	-5.497***	-5.425***	-5.390***	-5.438***	-5.322***
	(0.288)	(0.289)	(0.288)	(0.288)	(0.288)	(0.288)
Related Density (RD)	0.186***	0.186***	0.186***	0.187***	0.187***	0.187***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
RD*tot.rd				0.021***		
				(0.003)		
RD*tot.rd.collab					0.022***	
					(0.003)	
RD*tot.rd.non.collab						0.020***
						(0.003)
Constant	0.976***	0.979***	0.973***	0.969***	0.973***	0.964***
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
Observations	27,069	27,069	27,069	27,069	27,069	27,069
R^2	0.279	0.279	0.281	0.281	0.281	0.282
Adjusted R^2	0.279	0.279	0.280	0.280	0.281	0.282
Residual Std. Error	0.414 (df = 27063)	0.414 (df = 27063)	0.413 (df = 27063)	0.413 (df = 27062)	0.413 (df = 27062)	0.413 (df = 27062)
F Statistic	2,092.438*** (df = 5; 27063)	2,094.336*** (df = 5; 27063)	2,110.527*** (df = 5; 27063)	1,758.455*** (df = 6; 27062)	1,761.349*** (df = 6; 27062)	1,772.286*** (df = 6; 27062)
Note:						*p**p***p<0.01

In Appendix 4, we show the same estimations for co-financing firms (Table A4.1) and subsidized firms (Table A4.2). Findings in Table A4.1 for co-financing firms are almost identical as in Table 4. The same applies to the findings for subsidized firms in Table A4.2.

The previous tables have so far assessed all VINNOVA R&D programs. We have done the same analyses for two of the largest programs, the Vehicles program and the Vinnova Excellent Centre program.

The Vehicles program is the largest of all VINNOVA programs and directed at the automotive industry. As shown in Table 1, it consisted of 258 projects in total, with an average of 5 participating actors. This program consists of very few non-collaborative projects (almost all of them are collaborative projects) which means that we do not have a sufficient amount of observations to make a distinction between the two types of R&D projects in the estimations. Tables 5 and 6 indicate that R&D grants in the Vehicle program do have more of an impact on technology entry than on industry entry in Swedish regions.

Table 5. Regional entry of industry (5-digit) in the Vehicles program: role of local capabilities and total R&D grants (all firms)

	Dependent variable:	
	Entry	
	(1)	(2)
tot.rd (log)	0.005**	-0.0004
	(0.003)	(0.003)
workers_uni	-0.0003	-0.0002
	(0.004)	(0.004)
Grp	-0.010**	-0.010**
	(0.005)	(0.005)
sh.stem	0.133	0.124
	(0.140)	(0.140)
Related Density (RD)	0.028***	0.029***
	(0.002)	(0.002)
RD*tot.rd		0.014***
		(0.004)
Constant	0.063***	0.063***
	(0.007)	(0.007)
Observations	20,407	20,407
R^2	0.011	0.011
Adjusted R^2	0.010	0.011
Residual Std. Error	0.244 (df = 20401)	0.244 (df = 20400)
F Statistic	44.154*** (df = 5; 20401)	38.830*** (df = 6; 20400)
Note:		*p**p***p<0.01

Table 6. Regional entry of technology (4-digit) in the Vehicles program: role of local capabilities and total R&D grants (all firms)

	Dependent variable:	
	Entry	
	(1)	(2)
tot.rd (log)	0.008***	0.014***
	(0.003)	(0.003)
workers_uni	-0.023**	-0.022**
	(0.010)	(0.010)
Grp	-0.072***	-0.074***
	(0.010)	(0.010)
sh.stem	-5.574***	-5.598***
	(0.293)	(0.293)
Related Density (RD)	0.187***	0.187***
	(0.003)	(0.003)
RD*tot.rd		0.013***
		(0.003)
Constant	0.985***	0.987***
	(0.025)	(0.025)
Observations	27,060	27,060
R^2	0.279	0.279
Adjusted R^2	0.278	0.279
Residual Std. Error	0.414 (df = 27054)	0.414 (df = 27053)
F Statistic	2,089.888*** (df = 5; 27054)	1,747.746*** (df = 6; 27053)
Note:		*p**p***p<0.01

In Tables 7 and 8, we look at the VINN Excellence Centre program. This program supports basic, industry-related research in 17 research centres at universities, colleges and institutes, consisting of 38 projects that have an average of 9.1 participants per project (see Table 1). In this program, all projects are collaborative. The findings show that R&D grants in the VINN Excellence Centre program correlate with the entry of both new technologies and new industries in Swedish regions.

Table 7. Regional entry of industry (5-digit) in the VINN Excellence Centre program: role of local capabilities and total R&D grants (all firms)

	Dependent variable:	
	Entry	
	(1)	(2)
tot.rd (log)	0.009***	0.008***
	(0.003)	(0.003)
workers_uni	-0.0001	-0.0001
	(0.004)	(0.004)
Grp	-0.010**	-0.010**
	(0.005)	(0.005)
sh.stem	0.130	0.129
	(0.140)	(0.140)
Related Density (RD)	0.028***	0.028***
	(0.002)	(0.002)
RD*tot.rd		0.002
		(0.003)
Constant	0.063***	0.063***
	(0.007)	(0.007)
Observations	20,389	20,389
R^2	0.011	0.011
Adjusted R^2	0.011	0.011
Residual Std. Error	0.244 (df = 20383)	0.244 (df = 20382)
F Statistic	45.457*** (df = 5; 20383)	37.936*** (df = 6; 20382)
Note:		*p**p***p<0.01

Table 8. Regional entry of technology (4-digit) in the VINN Excellence Centre program: role of local capabilities and total R&D grants (all firms)

	Dependent variable:	
	Entry	
	(1)	(2)
tot.rd (log)	0.011***	0.015***
	(0.003)	(0.003)
workers_uni	-0.023**	-0.023**
	(0.010)	(0.010)
Grp	-0.074***	-0.076***
	(0.010)	(0.010)
sh.stem	-5.469***	-5.421***
	(0.289)	(0.289)
Related Density (RD)	0.186***	0.188***
	(0.003)	(0.003)
RD*tot.rd		0.014***
		(0.003)
Constant	0.976***	0.972***
	(0.025)	(0.025)
Observations	27,059	27,059
R^2	0.279	0.279
Adjusted R^2	0.279	0.279
Residual Std. Error	0.414 (df = 27053)	0.414 (df = 27052)
F Statistic	2,090.911*** (df = 5; 27053)	1,747.988*** (df = 6; 27052)
Note:		*p**p***p<0.01

So far, we have analyzed the effects of R&D subsidies to firms and co-financing by firms. But how about the possible effect of R&D subsidies to non-firms on regional diversification?

To investigate this, we created a variable subsidy_nonfirms_distrib (log) that captures R&D subsidies to a non-firm that are distributed within the region to industries based on the firms participating in the project, regardless of where those firms were located, weighted according to their co-financing. The variable subsidy_nonfirms_distrib_coord (log) is the same type of variable but only includes subsidies to non-firms that were the project leader/coordinator. We also constructed a variable called subsidy_nonfirms_indirect that assigns the subsidies given to non-firms to the firms that participate in the project, based on their co-financing, and in the region(s) where the firms were located. Thus, if university X receives SEK 10 mn in a given project, and firm Y contributes 50 % of the co-financing in the project, then firm Y will receive SEK 5 mn as an indirect subsidy. We also have a variable cofin_nonfirms (log) that refers to co-financing contributed by non-firms, in thousands of SEK.

As shown in Table 9, none of the subsidy variables is significant in the industry entry model, except for one. Subsidy_nonfirms_indirect is the only variable with a positive and significant coefficient. Table 10 suggests that R&D grants to non-local firms may have some positive impact on technological diversification in regions. However, one subsidy variable shows a negative sign. Overall, the analyses suggest that R&D grants to non-firms seem to matter for technological diversification, not industrial diversification. This is not unexpected, as R&D grants to universities (which take up the main part of the R&D grants to non-firms) are more likely to increase patenting in a region rather than employment growth in a region.

Table 9. Regional entry of industry (5-digit): the role of local capabilities and R&D grants to non-local firms

	Dependent variable:			
	Entry			
	(1)	(2)	(3)	(4)
subsidy_nonfirms_distrib (log)	-0.002			
	(0.002)			
subsidy_nonfirms_distrib_coord (log)		-0.001		
		(0.002)		
subsidy_nonfirms_indirect (log)			0.010^{***}	
			(0.002)	
cofin_nonfirms (log)				0.001
				(0.002)
workers_uni	-0.001	-0.001	-0.0004	-0.001
	(0.004)	(0.004)	(0.004)	(0.004)
grp	-0.009^{**}	-0.009^{**}	-0.010^{**}	-0.009^{**}
	(0.005)	(0.005)	(0.005)	(0.005)
sh.stem	0.139	0.137	0.119	0.132
	(0.140)	(0.140)	(0.140)	(0.140)
Related Density (RD)	0.028^{***}	0.028^{***}	0.028^{***}	0.028^{***}
	(0.002)	(0.002)	(0.002)	(0.002)
Constant	0.062^{***}	0.062^{***}	0.064^{***}	0.062^{***}
	(0.007)	(0.007)	(0.007)	(0.007)
Observations	20,453	20,453	20,453	20,453
R^2	0.011	0.011	0.011	0.011
Adjusted R^2	0.010	0.010	0.011	0.010
Residual Std. Error (df = 20447)	0.244	0.244	0.243	0.244
F Statistic (df = 5; 20447)	43.668^{***}	43.567^{***}	46.836^{***}	43.514^{***}
Note:				*p**p***p<0.01

Table 10. Regional entry of technology (4-digit): role of local capabilities and R&D grants to non-local firms

	Dependent variable:			
	Entry			
	(1)	(2)	(3)	(4)
subsidy_nonfirms_distrib (log)	0.010***			
	(0.003)			
subsidy_nonfirms_distrib_coord (log)		0.012***		
		(0.003)		
subsidy_nonfirms_indirect (log)			0.012***	
			(0.003)	
cofin_nonfirms (log)				-0.005*
				(0.003)
workers_uni	-0.025**	-0.025**	-0.025**	-0.025**
	(0.010)	(0.010)	(0.010)	(0.010)
Grp	-0.071***	-0.072***	-0.072***	-0.071***
	(0.010)	(0.010)	(0.010)	(0.010)
sh.stem	-5.485***	-5.516***	-5.488***	-5.430***
	(0.289)	(0.289)	(0.289)	(0.288)
Related Density (RD)	0.187***	0.186***	0.187***	0.187***
	(0.003)	(0.003)	(0.003)	(0.003)
Constant	0.977***	0.980***	0.978***	0.972***
	(0.025)	(0.025)	(0.025)	(0.025)
Observations	27,069	27,069	27,069	27,069
R^2	0.279	0.279	0.279	0.278
Adjusted R^2	0.278	0.279	0.279	0.278
Residual Std. Error (df = 27063)	0.414	0.414	0.414	0.414
F Statistic (df = 5; 27063)	2,089.920***	2,091.761***	2,091.164***	2,086.520***
Note:				*p**p***p<0.01

5. Conclusions

This study has addressed the question whether public R&D grants tend to lead to the development of new specializations in a region, rather than the strengthening of existing specialization in a region. There is increasing awareness that regions need to diversify into new activities, in order to cope with the stagnation and decline of existing activities in the region. The main research question of the study was therefore the following: is there evidence that R&D grants may induce the development of new activities in Swedish regions?

We investigated whether there is a correlation between research and innovation programs implemented by VINNOVA in the period 2010-2012 on the one hand, and the development of new industries and new technologies in Swedish regions in the years after on the other hand. We examined whether Swedish regions that receive more R&D funding in a specific industry or technology are also more likely to develop a new specialization in this industry and technology. We also tested whether there is a difference between collaborative and non-collaborative R&D projects. Finally, we analysed whether R&D grants are able to promote regional diversification when there is a lack of relevant local capabilities in a region.

The main findings can be summarized as follows.

First of all, as expected, we find strong evidence that local pre-existing capabilities strongly condition the industrial and technological evolution of Swedish regions. The coefficient of Relatedness Density appeared to be positive and significant in all specifications, with no exception. This confirms findings of other studies that regions tend to diversify in new activities that are strongly related to existing activities in regions (Boschma 2017; Hidalgo et al. 2018).

Second, we show that regions receiving R&D grants in VINNOVA programs in a specific industry and a specific technology are more likely to diversify into this industry and technology. We found a positive and significant coefficient in almost all specifications, especially for technological diversification. However, we could not find such a relationship between R&D grants and industrial diversification in the Vehicles program. We also made a distinction between R&D grants to firms and R&D grants to non-firms. The analyses showed that R&D grants to non-firms (most of them concern universities) seem to matter for technological diversification, not industrial diversification. This does not come as a surprise, as R&D grants to universities are more likely to increase regional patenting rather than employment, especially in the short-run.

Third, regions with more collaborative R&D grants in VINNOVA programs are more likely to diversify into new industries and technologies. This finding of a positive correlation between collaborative R&D grants and regional diversification is in line with literature stressing the importance of research collaboration for innovation and renewal (Czarnitzki and Hussinger 2018). In contrast, we did not find a general tendency of regions with more non-collaborative grants to diversify into new industries in Sweden. However, we found a positive relationship between non-collaborative grants and the development of new technologies in Swedish regions.

Fourth, we found that the relationship between R&D grants and regional diversification is strongest when relevant local capabilities are present in the region. In almost all specifications, the coefficients of the interaction terms were positive and significant. Even when we found no direct relationship between non-collaborative grants and industrial diversification in regions, we still found a positive and significant coefficient of the interaction term. A plausible interpretation of this result is that non-collaborative grants could still favour the development of new industries in Swedish regions, but only where relevant local capabilities are present. In sum, we did not find evidence of a relationship between R&D grants and regional diversification when there is a lack of relevant local capabilities.

If we compare the results for industrial and technological diversification, we observe that R&D grants are more likely to be associated with technological diversification, and less so with industrial diversification in regions. This is not unexpected: R&D grants are more likely to generate new knowledge that lead to new patents and the development of new technologies, but not necessarily to employment growth and the development of new industries in a region in the short run.

A key objective of the study was to analyze different VINNOVA research and innovation programs at the same time. We also looked more in detail to two of the largest programs, the Vehicles program and the VINN Excellence Centre program. The Vehicles program is directed at the automotive industry, while the VINN Excellence Centre program supports fundamental, industry-related research in research centres like universities. The findings suggest that R&D grants in the VINN Excellence Centre program can be associated with the entry of both new technologies and new industries in Swedish regions. R&D grants in the Vehicle program seem to support the entry of new technologies, rather than the entry of new industries in regions.

We see this study as a first step towards assessing the full impact of R&D grants on diversification of the Swedish economy. Our study aimed to explore the relationship (or correlation) between R&D grants and technological and industrial diversification in Swedish regions, rather than demonstrating a causal link between the two. One also has to remind that we examined only R&D programs initiated and run by VINNOVA, which take up a fraction of all R&D funding provided by the Swedish national government. Moreover, we have not accounted for the impact of international R&D grants (like the participation of Swedish regions in the EU Framework Programs) either. Including those R&D programs would be a next step to take full account of the effects of R&D grants on regional diversification.

This study has primarily been interested in assessing the possible effect of public R&D grants on new specializations in regions. A next step is to examine the effect on existing specializations in regions, and whether this effect is possibly stronger when related activities are present in the region. This may be important, as many VINNOVA programs focus on promoting excellence. Another important next step would be to estimate an indirect effect of R&D grants on the development of related activities in the region. That is, if Lund receives R&D funding in nano-technology, will this have an effect on the development of activities related to nano-tech in Lund and in other regions that participated in the R&D project? And finally, we need to explore more in detail why we found that the relationship between R&D grants and regional diversification is stronger when relevant local capabilities are present. Is it because R&D grants that target closely related activities in the region are more successful, or because R&D grants that aim for less related activities in regions are more likely to fail, or are both true?

Despite all these remarks of caution, we still think we can draw some policy implications.

First of all, the relatedness framework applied in this study may have some interesting implications for policy that are closely related, but still slightly different from the conventional wisdom behind research and innovation policy. For instance, it might be recommendable to define the objective of R&D policy more in terms of developing new specializations in regions (rather than supporting existing specializations). This may be a way to go around market power and vested interests that might otherwise frustrate innovation and structural change in regions. Moreover, as actors tend to show risk-adverse behavior and incentives for innovation tend to be lower when risks are higher, the relatedness approach provides a policy framework in which risks attached to diversification become lower the more relevant capabilities are present in the region (Balland et al. 2019a). This might increase the willingness of actors to create new things but it may also increase the effectiveness of R&D policy, as our study suggests.

It seems that R&D grants may be a useful policy tool to make Swedish regions diversify into new activities. The advantage of R&D grants as a policy tool is that it can be targeted to specific technologies and industries that public policy wants to promote, like in the current set-up of Smart Specialization policy in the European Union (Balland et al. 2019a). Moreover, the study also showed that collaborative R&D grants matter especially for regional diversification. The advantage of using collaborative R&D grants as a policy tool is that it promotes interaction across different activities deemed crucial for innovation and diversification in regions. This requires a careful selection of partners in publicly funded R&D projects. This is in line with studies that show it is crucial for innovation to bring in the right partners in collaborative research networks in terms of (related) variety of competences (Fleming et al. 2007; Gilsing et al. 2007; Cassi and Plunket 2015).

The results of the study also indicated that R&D grants have more of an impact on the development of new technologies rather than new industries in regions, at least in the short run. This implies that, on top of R&D grants, other policy actions (like new regulations or stimulating supply of venture capital) might be needed to ensure that R&D grants will not only lead to new knowledge and technologies, but that these are also transformed into economic development and the creation of new firms and new economic sectors.

Finally, a key finding of the study was that the possible effects of public support of R&D are not independent of the local capabilities in a region. This may imply that public research and innovation programs need to account for local capabilities. There are divergent views on that. On the one hand, R&D programs might make more sense when they target new activities in which a Swedish region has high potential due to the presence of relevant capabilities. R&D policy is more likely to be effective when it avoids building new activities in regions from scratch, as this study also tends to suggest. On the other hand, one could argue that R&D grants should focus more on radical change (i.e. less related diversification), as the market will not take up easily R&D projects that are very risky, and regions might become locked-in in old and mature specializations (Crespo et al. 2014).

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Appendix 1. Variable list

Variable name	Description
Technology Entry	1 if a technology i that did not belong to the portfolio of the region r at period 2009-2013 enters the region in period 2014-2018, otherwise it gets a score of 0.
Industry Entry	1 if an industry i that did not belong to the portfolio of region r in period 2011-2013 enters the region in period 2014-2016, otherwise it gets a score of 0.
Related Density (RD)	sum of relatedness of technology/industry i to all other technologies/industries j in which the region has a Relative Technological/Industrial Advantage, divided by sum of relatedness of technology/industry i to all other technologies/industries j in the reference group in 2012.
tot.rd (log)	direct R&D subsidies to firms plus co-financing by firms in industry-region 2010-2012, in thousands of SEK.
tot.rd.collab (log)	direct R&D subsidies to firms in collaborative projects plus co-financing to collaborative projects by firms in industry-region 2010-2012, in thousands of SEK.
tot.rd.non.collab (log)	direct R&D subsidies to firms in non-collaborative projects plus co-financing to non-collaborative projects by firms in industry-region 2010-2012, in thousands of SEK.
cofin_firms (log)	co-financing contributed to VINNOVA projects by firms in industry-region 2010-2012, in thousands of SEK.
cofin_firms_collab (log)	co-financing to collaborative projects by firms in industry-region 2010-2012, in thousands of SEK.
cofin_firms_noncollab (log)	co-financing to non-collaborative projects by firms in industry-region 2010-2012, in thousands of SEK.
subsidy_firms (log)	direct R&D subsidies in industry-region 2010-2012, in thousands of SEK.
subsidy_firms_collab (log)	direct R&D subsidies to firms in collaborative projects in industry-region 2010-2012, in thousands of SEK.
subsidy_firms_noncollab (log)	direct R&D subsidies to firms in non-collaborative projects in industry-region 2010-2012, in thousands of SEK.
subsidy_nonfirms_distrib (log)	R&D subsidies to non-firms in industry-region 2010-2012, distributed to industries based on firms' co-funding, in thousands of SEK.
subsidy_nonfirms_distrib_coord (log)	same, but only for subsidies to project coordinator leader, in thousands of SEK.

subsidy_nonfirms_indirect (log)	R&D subsidies to non-firms 2010-2012, assigned to the industry-regions of the firms in project based on their co-financing, in thousands of SEK.
cofin_nonfirms (log)	co-financing contributed by non-firms in region 2010-2012, in thousands of SEK.
workers_uni	number of workers in higher education (NACE 854) in a region in 2012.
Grp	gross regional product, SEK millions in 2012.
sh.stem	number of workers with STEM college education (>2 years) in a region in 2012.

Appendix 2. Descriptive statistics

To be completed

Appendix 3. Regional entry of industry (5-digit): role of local capabilities and total R&D grants

In Appendix 3, we show the same estimations as in Table 3, but now for co-financing firms (Table A3.1) and subsidized firms (Table A3.2) separately. Table A3.1 looks at co-financing only, and includes the following three subsidy variables: (1) cofin_firms (log): co-financing contributed to VINNOVA projects by firms, in thousands of SEK; (2) cofin_firms (log)_collab: co-financing to collaborative projects by firms, in thousands of SEK; (3) cofin_firms_noncollab (log): co-financing to non-collaborative projects by firms, in thousands of SEK.

As shown in Table A3.1, the findings are almost identical as in Table 3. Again, the coefficient of relatedness is positive and significant, and regions that receive R&D grants in a specific industry are more likely to diversify into this industry. The coefficients of the interaction variables are positive and significant, with the exception of the last interaction variable.

Table A3.1. Regional entry of industry (5-digit): role of local capabilities and total R&D grants (cofin firms)

	Dependent variable:					
	Entry					
	(1)	(2)	(3)	(4)	(5)	(6)
cofin_firms (log)	0.009***			0.007***		
	(0.002)			(0.002)		
cofin_firms_collab (log)		0.010***			0.008***	
		(0.002)			(0.003)	
cofin_firms_noncollab (log)			0.004*			0.003
			(0.002)			(0.002)
workers_uni	-0.0004	-0.0003	-0.001	0.00000	0.00001	-0.0004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Grp	-0.011**	-0.011**	-0.010**	-0.011**	-0.011**	-0.010**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
sh.stem	0.123	0.122	0.129	0.111	0.112	0.126
	(0.140)	(0.140)	(0.140)	(0.140)	(0.140)	(0.140)
Related Density (RD)	0.028***	0.028***	0.028***	0.029***	0.029***	0.028***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
RD*cofin_firms				0.007**		
				(0.003)		
RD*cofin_firms_collab					0.007**	
					(0.003)	
RD*cofin_firms_noncollab						0.003
						(0.003)
Constant	0.063***	0.064***	0.063***	0.064***	0.064***	0.063***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Observations	20,453	20,453	20,453	20,453	20,453	20,453
R^2	0.011	0.011	0.011	0.012	0.012	0.011
Adjusted R^2	0.011	0.011	0.010	0.011	0.011	0.010
Residual Std. Error	0.243 (df = 20447)	0.243 (df = 20447)	0.244 (df = 20447)	0.243 (df = 20446)	0.243 (df = 20446)	0.244 (df = 20446)
F Statistic	46.447*** (df = 5; 20447)	46.856*** (df = 5; 20447)	44.157*** (df = 5; 20447)	39.737*** (df = 6; 20446)	40.100*** (df = 6; 20446)	37.018*** (df = 6; 20446)
Note:						*p**p***p<0.01

Table A3.2 looks at firms receiving subsidies, not at firms involved in co-financing, and includes the following three subsidy variables: (1) subsidy_firms (log): direct R&D subsidies, in thousands of SEK; (2) subsidy_firms_collab (log): direct R&D subsidies to firms in collaborative projects, in thousands of SEK; (3) subsidy_firms_noncollab (log): direct R&D subsidies to firms in non-collaborative projects, in thousands of SEK.

Findings are similar as in Table 3, with one major exception. The coefficient of collaborative R&D grants is not significant anymore, like non-collaborative grants. However, the coefficients of the interaction variables are positive and significant, showing that the effects of collaborative and non-collaborative R&D subsidies becomes only manifest when relatedness is higher.

Table A3.2. Regional entry of industry (5-digit): role of local capabilities and total R&D grants (subsidy firms)

	Dependent variable:					
	Entry					
	(1)	(2)	(3)	(4)	(5)	(6)
subsidy_firms (log)	0.005**			0.004*		
	(0.002)			(0.002)		
subsidy_firms_collab (log)		0.002			0.002	
		(0.002)			(0.002)	
subsidy_firms_noncollab (log)			0.006***			0.003
			(0.002)			(0.002)
workers_uni	-0.001	-0.001	-0.001	-0.0002	-0.0004	-0.0002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Grp	-0.010**	-0.010**	-0.010**	-0.010**	-0.010**	-0.010**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Stem	0.125	0.131	0.126	0.115	0.126	0.117
	(0.140)	(0.140)	(0.140)	(0.140)	(0.140)	(0.140)
Related Density (RD)	0.028***	0.028***	0.028***	0.028***	0.028***	0.028***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
RD*subsidy_firms				0.006**		
				(0.003)		
RD*subsidy_firms_collab					0.005*	
					(0.003)	
RD*subsidy_firms_noncollab						0.007**
						(0.003)
Constant	0.063***	0.063***	0.063***	0.063***	0.063***	0.063***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Observations	20,453	20,453	20,453	20,453	20,453	20,453
R^2	0.011	0.011	0.011	0.011	0.011	0.011
Adjusted R^2	0.011	0.010	0.011	0.011	0.010	0.011
Residual Std. Error	0.244 (df = 20447)	0.244 (df = 20447)	0.244 (df = 20447)	0.244 (df = 20446)	0.244 (df = 20446)	0.244 (df = 20446)
F Statistic	44.683*** (df = 5; 20447)	43.687*** (df = 5; 20447)	44.843*** (df = 5; 20447)	38.150*** (df = 6; 20446)	36.917*** (df = 6; 20446)	38.288*** (df = 6; 20446)
Note:						*p**p***p<0.01

Appendix 4. Regional entry of technology (4-digit): role of local capabilities and total R&D grants

Table A.4.1 reports the main findings for 4-digit technologies for cofin firms only. The findings are almost identical as in Table 4.

Table A4.1. Regional entry of technology (4-digit): role of local capabilities and total R&D grants (cofin firms)

	Dependent variable:					
	Entry					
	(1)	(2)	(3)	(4)	(5)	(6)
cofin_firms (log)	0.013^{***}			0.020^{***}		
	(0.003)			(0.003)		
cofin_firms_collab (log)		0.015^{***}			0.023^{***}	
		(0.003)			(0.003)	
cofin_firms_noncollab (log)			0.025^{***}			0.032^{***}
			(0.003)			(0.003)
workers_uni	-0.026^{**}	-0.026^{**}	-0.028^{***}	-0.027^{**}	-0.026^{**}	-0.029^{***}
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
grp	-0.071^{***}	-0.071^{***}	-0.072^{***}	-0.073^{***}	-0.073^{***}	-0.073^{***}
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
sh.stem	-5.471^{***}	-5.509^{***}	-5.401^{***}	-5.397^{***}	-5.450^{***}	-5.305^{***}
	(0.288)	(0.289)	(0.288)	(0.288)	(0.288)	(0.288)
Related Density (RD)	0.186^{***}	0.186^{***}	0.186^{***}	0.187^{***}	0.187^{***}	0.186^{***}
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
RD*cofin_firms				0.021^{***}		
				(0.003)		
RD*cofin_firms_collab					0.021^{***}	
					(0.003)	
RD*cofin_firms_noncollab						0.021^{***}
						(0.003)
Constant	0.976^{***}	0.980^{***}	0.971^{***}	0.969^{***}	0.974^{***}	0.962^{***}
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
Observations	27,069	27,069	27,069	27,069	27,069	27,069
R^2	0.279	0.279	0.281	0.281	0.281	0.282
Adjusted R^2	0.279	0.279	0.281	0.280	0.281	0.282
Residual Std. Error	0.414 (df = 27063)	0.414 (df = 27063)	0.413 (df = 27063)	0.413 (df = 27062)	0.413 (df = 27062)	0.413 (df = 27062)
F Statistic	$2,092.378^{***}$ (df = 5; 27063)	$2,094.840^{***}$ (df = 5; 27063)	$2,111.831^{***}$ (df = 5; 27063)	$1,759.288^{***}$ (df = 6; 27062)	$1,761.584^{***}$ (df = 6; 27062)	$1,775.171^{***}$ (df = 6; 27062)
Note:						*p**p***p<0.01

Table A4.2 reports the main findings for 4-digit technologies for subsidized firms only. The findings are almost identical as in Tables 4 and A4.1.

Table A4.2. Regional entry of technology (4-digit): role of local capabilities and total R&D grants (subsidy firms)

	Dependent variable:					
	Entry					
	(1)	(2)	(3)	(4)	(5)	(6)
subsidy_firms (log)	0.019^{***}			0.027^{***}		
	(0.003)			(0.003)		
subsidy_firms_collab (log)		0.020^{***}			0.030^{***}	
		(0.003)			(0.003)	
subsidy_firms_noncollab (log)			0.026^{***}			0.032^{***}
			(0.003)			(0.003)
workers_uni	-0.027^{***}	-0.025^{**}	-0.028^{***}	-0.028^{***}	-0.027^{***}	-0.029^{***}
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
grp	-0.072^{***}	-0.073^{***}	-0.072^{***}	-0.073^{***}	-0.074^{***}	-0.074^{***}
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
sh.stem	-5.456^{***}	-5.539^{***}	-5.427^{***}	-5.344^{***}	-5.440^{***}	-5.327^{***}
	(0.288)	(0.288)	(0.288)	(0.288)	(0.288)	(0.288)
Related Density (RD)	0.186^{***}	0.186^{***}	0.186^{***}	0.187^{***}	0.187^{***}	0.186^{***}
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
RD*subsidy_firms				0.022^{***}		
				(0.003)		
RD*subsidy_firms_collab					0.030^{***}	
					(0.003)	
RD*subsidy_firms_noncollab						0.019^{***}
						(0.003)
Constant	0.975^{***}	0.982^{***}	0.973^{***}	0.966^{***}	0.974^{***}	0.964^{***}
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
Observations	27,069	27,069	27,069	27,069	27,069	27,069
R^2	0.280	0.280	0.281	0.281	0.283	0.282
Adjusted R^2	0.279	0.279	0.281	0.281	0.283	0.282
Residual Std. Error	0.414 (df = 27063)	0.414 (df = 27063)	0.413 (df = 27063)	0.413 (df = 27062)	0.413 (df = 27062)	0.413 (df = 27062)
F Statistic	$2,100.694^{***}$ (df = 5; 27063)	$2,100.893^{***}$ (df = 5; 27063)	$2,112.898^{***}$ (df = 5; 27063)	$1,767.005^{***}$ (df = 6; 27062)	$1,780.548^{***}$ (df = 6; 27062)	$1,772.959^{***}$ (df = 6; 27062)
Note:						*p**p***p<0.01

Appendix 5. Regional entry of industry and technology (2-digit): role of local capabilities and total R&D grants

Appendix 5 presents the same estimations as Tables 3 and 4, but not for 5-digit industries and 4-digit technologies but instead for 2-digit industries (Table A5.1) and 2-digit technologies (Table A5.2). The findings are almost identical to Tables 3 and 4. There is one exception. The non-collaborative R&D projects are not significant anymore in the regional entry of technologies at the 2-digit level in Table A5.2.

Table A5.1. Regional entry of industry (2-digit): role of local capabilities and total R&D grants (all firms)

	Dependent variable:					
	entry					
	(1)	(2)	(3)	(4)	(5)	(6)
tot.rd (log)	0.014^{***}			0.011^{**}		
	(0.005)			(0.005)		
tot.rd.collab (log)		0.016^{***}			0.014^{***}	
		(0.005)			(0.005)	
tot.rd.non.collab (log)			0.004			0.001
			(0.005)			(0.005)
workers_uni	-0.013	-0.013	-0.012	-0.012	-0.012	-0.011
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
grp	0.011	0.010	0.012	0.009	0.009	0.011
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
sh.stem	-0.329	-0.341	-0.268	-0.357	-0.357	-0.302
	(0.314)	(0.313)	(0.314)	(0.314)	(0.314)	(0.314)
Related Density (RD)	0.014^{***}	0.014^{***}	0.014^{***}	0.016^{***}	0.015^{***}	0.016^{***}
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
RD*tot.rd				0.011^{*}		
				(0.005)		
RD*tot.rd.collab					0.009^{*}	
					(0.006)	
RD*tot.rd.non.collab						0.011^{**}
						(0.006)
Constant	0.064^{***}	0.065^{***}	0.061^{***}	0.064^{***}	0.065^{***}	0.061^{***}
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Observations	3,133	3,133	3,133	3,133	3,133	3,133
R^2	0.007	0.008	0.005	0.009	0.009	0.006
Adjusted R^2	0.006	0.007	0.003	0.007	0.007	0.004
Residual Std. Error	0.210 (df = 3127)	0.210 (df = 3127)	0.210 (df = 3127)	0.210 (df = 3126)	0.210 (df = 3126)	0.210 (df = 3126)
F Statistic	4.595^{***} (df = 5; 3127)	5.142^{***} (df = 5; 3127)	3.004^{**} (df = 5; 3127)	4.469^{***} (df = 6; 3126)	4.772^{***} (df = 6; 3126)	3.188^{***} (df = 6; 3126)
Note:						*p**p***p<0.01

Table A5.2. Regional entry of technology (2-digit): role of local capabilities and total R&D grants (all firms)

	Dependent variable:					
	entry					
	(1)	(2)	(3)	(4)	(5)	(6)
tot.rd (log)	0.007***			0.006***		
	(0.002)			(0.002)		
tot.rd.collab (log)		0.006***			0.005**	
		(0.002)			(0.002)	
tot.rd.non.collab (log)			0.003			0.0005
			(0.002)			(0.002)
workers_uni	-0.058***	-0.058***	-0.057***	-0.057***	-0.057***	-0.057***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
grp	-0.013***	-0.012***	-0.012**	-0.013***	-0.014***	-0.014***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
sh.stem	-7.628***	-7.633***	-7.611***	-7.618***	-7.605***	-7.590***
	(0.179)	(0.179)	(0.179)	(0.179)	(0.179)	(0.179)
Related Density (RD)	0.054***	0.054***	0.054***	0.054***	0.054***	0.054***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
RD*tot.rd				-0.002		
				(0.002)		
RD*tot.rd.collab					-0.004**	
					(0.002)	
RD*tot.rd.non.collab						-0.005***
						(0.002)
Constant	0.912***	0.912***	0.911***	0.911***	0.911***	0.909***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Observations	40,799	40,799	40,799	40,799	40,799	40,799
R^2	0.271	0.271	0.271	0.271	0.271	0.271
Adjusted R^2	0.271	0.271	0.271	0.271	0.271	0.271
Residual Std. Error	0.383 (df = 40793)	0.383 (df = 40793)	0.383 (df = 40793)	0.383 (df = 40792)	0.383 (df = 40792)	0.383 (df = 40792)
F Statistic	3,032.991*** (df = 5; 40793)	3,032.388*** (df = 5; 40793)	3,029.689*** (df = 5; 40793)	2,527.711*** (df = 6; 40792)	2,528.196*** (df = 6; 40792)	2,527.035*** (df = 6; 40792)
Note:						*p**p***p<0.01

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