Does Centrality of Specialized Inventors Foster Regional Innovation? The case of Swiss medical device sector

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Abstract

The role of collaboration networks of inventors on innovation is a relevant topic in literature. Nevertheless, empirical findings are still limited. The paper examines how the level of collaboration of technologically specialized and academic inventors affects the innovation in the Swiss medical device sector at regional level. Our analysis reveals the importance of technological characterization of nodes when studying the impact of the network structure on innovation. The main findings in our empirical context are that: (1) at regional level, centrality of inventors specialized in medical devices and related technologies fosters the production of innovation in the medical device sector, (2) connectedness of specialized inventors across region does not forester innovation, and (3) centrality of academic inventors do not impact on the innovative performance of the region.

1. Introduction

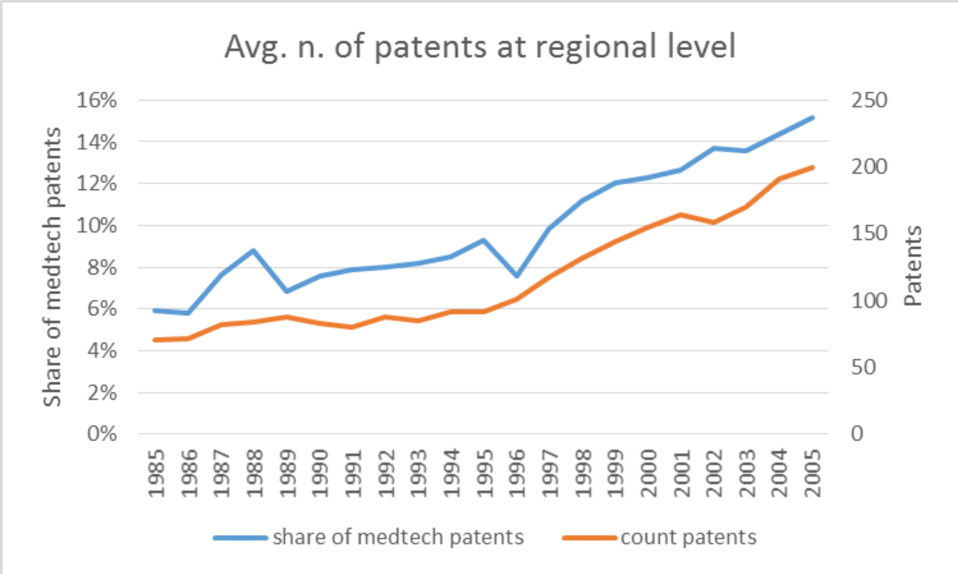
Specificities of individuals and the nature of their interactions are strictly connected to the shape of the large-scale social structure of their community (Granovetter, 1973). At the same time the position of a single individual within the network influences his ability to generate new ideas and his creativity (Burt, 2004).

A branch of innovation literature has recently focused on the influence of the network structure on the innovative performance of inventors at regional level. Scholars aim at identifying which characteristics of the social network structure enhance innovation. Among others (Fleming, King, & Juda, 2007) and (S Breschi & Lenzi, 2012) analyze how the structural characteristics of the network of inventors affect innovation by testing the "small world" hypothesis (Watts and Strogatz 1998). These studies usually consider individuals as homogeneous entities characterized only by only for their position within the network (with some exceptions (Lissoni et al. 2011)). This paper examines the impact of structural characteristic of the network on innovation by clustering the nodes (inventors) according to their technological specialization and their academic status. In other words, we assess how the position within the network of technologically specialized inventors and academic inventors impacts on the innovative performance of the region.

We concentrate our attention on the Swiss medical device sector[4] (MedTech). The MedTech sector despite its dimension has been largely neglected by the past literature. Previous works on networks of inventors have focused mainly on the biotech sector (Acharya R., Arundel A., 1998)(Zucker, Darby, & Brewer, 1994)(Owen-Smith & Powell, 2004) (Gertler & Levitte, 2005). MedTech represents about the 7% of the total amount of patents granted each year. Figure 1 shows the relevance of the sector in Switzerland during the time span 1985-2005.

4 The Food and Drug administration defines a medical devise as: "an instrument, apparatus, implement, machine, contrivance, implant, in vitro reagent, or other similar or related article, including a component part, or accessory which is: recognized in the official National Formulary, or the United States Pharmacopoeia, or in any supplement to them; intended for use in the diagnosis of disease or other conditions, or in the cure, mitigation, treatment, or prevention of disease, in humans or other animals; intended to affect the structure or any function of the body of humans or other animals, and which does not achieve its primary intended purposes through chemical action within or on the body of humans or other animals and which is not dependent upon being metabolized for the achievement of any of its primary intended purposes."

Figure 1: Average number of Swiss patents and share of patents in the Swiss medical device sector (MedTech) at regional level



The paper is organized as follows. Section 2 summarizes the empirical findings of the previous literature and presents our theoretical framework. Section 3 describes the dataset and the methodology. Section 4 presents the results. Section 5 concludes.

2. The role of specialized and academic inventors in the Swiss medical device sector

Characteristics of MedTech technology

The importance of knowledge flows among inventors in the creation of innovation is widely recognized (Romer, 1986). We can classify two kinds of knowledge according to the possibility of its codification. First, explicit knowledge can be transmitted among individuals in an objective way, for instance through written documents and technical reports. Tacit knowledge, on the contrary, is something that cannot be formalized and that depends on the experience (Collins, 2010). Tacit knowledge exchange is based on face-to-face interactions between individuals (Robin Cowan & Jonard, 2004). The following anecdote describes why the tacit process of knowledge transfer should be considered predominant in the MedTech sector.

In the early 1950s, in Zurich, an orthopedic surgeon, Maurice Müller decided to produce new orthopedic devices and in order to do that, he got in contact with Rober Mathys, an engineer who had a small metal processing factory specialized in the production of airplane instruments. Both these professionals need face-to-face contacts in order to profitably transfer each other their knowledge, abilities and skill. No formula or documentation that could have helped them in doing that. (Schlich, 2002).

MedTech knowledge can be considered also complex, in the sense of interdependence among its different parts. Complex knowledge do not go far from the source due to its difficulties of being transmitted (Sorenson et al., 2006). Moreover, complex knowledge cannot pass through actors if those actors are unable to understand and incorporate the message (Cohen and Levinthal, 1990). Contrary to complex knowledge, spreading simple knowledge does not need personal close interactions because the marginal cost of learning does not rise when the two actors are not in direct contact. Citing again anecdotal evidence in medtech sector:

it is possible to identify how different capabilities interweave: the needs of the surgeon must meet the characteristics of the materials, while the difficulties in seeing new uses for a material are overtaken by the vision, the creativity and the field experience of the surgeons.

Therefore, we consider Knowledge in Medtech sector as tacit and complex. This scenario suggests that frequent, continuous and numerous interactions are expected to maximize the probability of knowledge flows among individuals and then the probability of inventing and developing new medical devices.

However the interactions between inventors might have different effects according the inventors' technological specialization. The process of creation of a new medical devices is often a combination of knowledge coming from different fields that have to be adapted to meet the needs of diverse sectors. In his seminal work Schumpeter (1934) describes how recombination of knowledge affects the level of innovation: an invention is more likely if individuals with heterogeneous characteristic get in contact. Literature has dealt with the significance and recombination of knowledge. Scholars have recently focused on the importance of social connections between disciplines which are expected to foster creativity of individuals (Balconi, Breschi, & Lissoni, 2004). The idea that the heterogeneity in the social connections boost innovation is present also in the smart specialization framework[8]. Technological domains that are highly connected with other domains will offer greater possibilities for learning than less connected domains (Mccann & Ortega-Argilés, 2013). To recall the example of Swiss MedTech sector, since the very beginning of the medical devices industry, surgeons needed the help of specialized craftsman to develop their instruments:

the typical accuracy of the watchmakers must be rephrased in order to meet the needs of the dental industry, the awareness on the characteristics of the materials of a mechanical industry must be translated to understand which material can be better for a specific medical operation, the ability of computer scientists must be used to program robots so precise to accomplish a brain surgery and finally the surgeons must find a language to explain their desires to a non-medical audience (Schlich, 2002).

Then, we expect that the innovative process in MedTech sector requires a continuous exchange of information between specialists in different fields.

[8] Smart specialization is a new policy concept introduced by Prof. David, Foray, aims to define those areas where is prior to intervene with policy innovation activities within a regions. The central point of the smart specialization is the agent that has the capability to see where some help is needed: it is not anymore the policy maker that alone decides to whom the subvention is given but it is the entrepreneur that, living in direct contact with the real situation of the industry in that moment, can suggest where the interventions are more necessary.

Within region knowledge flows

We expect that a higher level of connection of inventors specialized in MedTech technologies might enhance the inventive productivity of the MedTech sector at regional level: well-connected inventors are more likely to experience the flow of tacit and complex knowledge from other inventors and to get in contact with knowledge from different fields. However, the multi field nature of MedTech technology might also determine the contribution to the innovative activity of the inventors specialized in other fields. We expect a positive impact on innovation of the centrality of inventors specialized in technologies that might contribute to the innovation in MedTech sectors (MedTech related inventors). We define two research hypotheses:

Hp1: Increased centrality of inventors specialized in MedTech technology correlates positively with the inventive performance of the region in MedTech.

Hp2: Increased centrality of inventors specialized in MedTech related technologies correlates positively with the inventive performance of the region in the MedTech sector.

Medtech sector, like the biotech sector, is "[…] a particularly rich area for examining university-industry interaction." (Rosenberg, 1994). However, contrary to the biotech sector, universities play a role in the development of new technologies "the 'D' of R&D" (Rosenberg, 1994) rather than in the research activity. In both sectors academic inventors are expected to play a relevant role in the innovation process, although in difference stage of the R&D.

Universities have been considered for long time the locus dedicated to the creation of basic knowledge while industry as the locus dedicated to the production of applied inventions and marketable products. Empirical studies have shown that academic inventors are frequently involved in collaboration with industry and also that their scientific productivity in terms of publications benefits from this interaction (Calderini, Franzoni, & Vezzulli, 2007) (Azoulay, Ding, & Stuart, 2009). Academic inventors are expected to act as brokers between different domains (Fleming, Colfer, Marin, & McPhie, 2001) and to be better connected than other inventors (Balconi et al., 2004). The presence of academic inventors is expected to enhance the inventive performance in MedTech sector due to their role of brokers between technologies and to their tendency of generating more connections that the average inventor in the field.

Hp3: Increased centrality of academic inventors correlates positively with the inventive performance of the region in the MedTech sector.

Across region knowledge flows

Empirical studies have shown that spatial proximity of inventors enhance the probability of knowledge flow: closely located inventors are more likely to meet, to collaborate and their cost of communication is lower (a. Agrawal, Cockburn, & McHale, 2006). Spatial proximity matters especially when the information that is transmitted is very articulated (Sorenson, Rivkin, & Fleming, 2006). These concepts have been used to explain the spontaneous creation of industrial clusters and the specialization of particular geographic areas. However, studies on agglomeration economies often neglect the possible external contribution of new and fresh knowledge coming from outside the localized industrial clusters (Bettencourt, Kaiser, & Kaur, 2009). Knowledge spillovers are particularly important in new sectors where fresh knowledge gives a fundamental contribution (Feldman & Audretsch, 1996). Then, level of innovation in a focal region might be affected by the knowledge flows from other regions. Several attempts have been done to measure knowledge spillovers from other regions and these attempts are characterized by heterogeneous results. The debate on the interpretation of results is still open. Cohen and Levinthal (1990) focus their attention on the uselessness of knowledge spillovers from other regions in absence of absorptive capacity of the metropolitan area. Other empirical findings confirms the positive effect of spillovers on the creation of innovation in the focal region. We expect that intense co-inventoship relations across region of specialized inventors and academic inventors might enhance the innovation in MedTech sector mainly for two reasons. First, co-inventorship and direct contacts between inventors facilitate knowledge flow given the intrinsic characteristics of MedTech technology (i.e. tacit and complex) and, second, flows of non-redundant knowledge from outside the region might facilitate innovation.

HP4: Increased centrality of specialized inventors (and academic inventors) connected to inventors from other regions correlates positively with the inventive performance of the region in the MedTech sector.

3. **Data and regression variables**

Data

The empirical approaches applied to study knowledge flows between inventors at regional level are quite heterogeneous. (Stefano Breschi & Lissoni, 2001) adopted a survey approach, (Jaffe 1993) relies on patent data and finally (Acharya R., Arundel A., 1998) based their analysis on interviews. In principle, in order to have a more comprehensive idea of the phenomenon of the social interactions between inventors we should take into account also the informal meetings, research contracts, recruiting and research activity (A. K. Agrawal, 2001). However, in MedTech sector, the patents and co-inventorship relations can be considered as an appropriate proxy of the social interactions. This is connected to the applied nature of the MedTech sector and to the limited impact of other forms of knowledge disclosure such as scientific publications. In order to test the applied nature of MedTech we show in table 1 the citations to non-patent literature compared to other Swiss industrial sectors.

Table1: Non-patent literature cited by patents in different field in Switzerland, form 1985 to 2005

field	total_npl	number_patents	average
Medtech	6036	4018	1.50224
Pharma	21478	5184	4.14313
Other machines	5718	3198	1.78799
Measurement	13890	5929	2.34272
Machines	4643	3018	1.53844
Biotech	16540	2543	6.50413

We include in our database all the applications at EPO classified the medical device sector[10] in Switzerland form 1985 to 2005[11]. We assign patents to a Swiss region according to the address

[10]We define "medical device patent" all those patent that have the first four digits of the International patent classifications (IPC) equal to: A61B, A61C, A61F, A61H, A61L, A61M, and A61N. In other words we do not take

reported by the inventors: a patent is assigned to a region if at least one inventor reports an address located in that region. In case two inventors of the same patent report two addresses located in different regions, we assign to each region the full credit of the patent. We reclassify the inventors in different patents according to their identity by using the CRIOS-Patstat DB (Tarasconi & Coffano, 2014). After the cleaning procedure we get 3196 distinct MedTech inventors, for a total of 5739 MedTech patents. We use these data to construct the inventors' networks for 26 regional areas (regional areas are defined according to the NUTS3[12] codes). We end up with a balanced panel made by 546 observations including 26 regions observed for 21 years.

Use of degree centrality

Literature shows different approaches to test the nexus between innovation at regional level and structure of the inventors' network. One of the most recent rely on the seminal works of Watts and Strogatz (1998) and Newman (2004). According to this approach, scholars aim to test the hypothesis that "small world"[14] network structure enhance innovation (Balconi et al., 2004) (Fleming et al., 2007). Networks characterize by "Small world" structures have dense and clustered connections between nodes that favor close collaboration of inventors. At the same time long ties connect different clusters in order to bring fresh and non-redundant information. The debate on the verification of small world hypothesis is still open and, according to the literature, there are at least four weaknesses in the empirical approaches applied. First, small world hypothesis is tested focusing on the largest network component. The largest component is a sub-graph which includes the largest number of connected nodes. However, the largest component is not representative of the whole network. According to Fleming, (2007) and Breschi, (2014), it includes on average the 20% of the nodes present in the entire network (in our study 18%). Second, sub-graphs smaller than the largest component are not considered even if they are of comparable size. Third the methodologies applied to test the small world hypothesis neglect the heterogeneity of nodes, treating them as homogeneous actors within the network. Finally, several works do not consider the variation of the size of the network over time: the network are open, so the number of nodes can increase or decrease over time (Barabási, 1999).

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those medical devices referred to animals and those medical devices related to transport or accommodation specially adapted for patients, because we think that these categories are not useful for our analysis. Moreover the number of patents in these subcategories is negligible.

[11]Data source: Patstat is the European patent office database. The version used for this work is the one of October 2013

[12] NUTS3 is the classification of territorial units for statistics in Europe.

[14]At the two extremes, networks are classified as regular or random network. However, real networks are something in between these two concepts. The small world structure is defined as clusters of locally dense interaction connected via a few bridging ties. This results in a very highly clustered network where nodes are very close because of long bridging ties. There are several examples of small world networks in everyday life: electric power grids, brain neurons connections and so on (Watts & Strogatz, 1998). The small world network has also peculiar characteristics like, a higher speed in the diffusion of the information, compared with a regular network. This is the reason why many scholars believe that the small world structure maximizes the network's capability to spread knowledge (Balconi et al., 2004) (Fleming et al., 2007). The predominant hypothesis is that this kind of networks should enhance innovative creativity (Fleming et al., 2007).

Similarly to the small world approach we consider the structural property of the network, although we rely on the measure of average degree centrality of the nodes in order to characterize the network structure. Differently from the measures applied to test the small world test, the degree centrality accounts for all the individuals in the network, including the isolated and the nodes not connected to the principal component.

We distinguish two networks of inventors, one based on the co-inventorship relations within the region and one based on the co-inventorship relation across the region. The former network is characterized by co-location of the inventors in the same region then, interactions among individuals are expected to carry redundant knowledge. On the contrary, the latter network, connects individuals located in different regions (industrial clusters) and then it is expected to be more likely to carry new and non-redundant knowledge. For both networks we calculates the average degree centrality of inventors at regional level.

We rely on the work of Borgatti (2005) for the choice of degree centrality measure. Brogatti distinguishes three different types of knowledge flows processes: transfer, serial duplication, and parallel duplication. In the transfer process, the object of the flow is indivisible and excludable (eg. a book). In the serial duplication and parallel duplication the object can be spread all over the network with differences in the possibility for an agent to be touched more than once by the same information[15]. The knowledge flows in MedTech sector can be classified as a parallel duplication process. This means that knowledge can be spread from one agent to many other agents at the same time. In the specific context of knowledge flow, the measure of degree connection takes a very specific meaning. It gives the risk for a node to be "infected" by the knowledge flow at time t+1 in a process that do not involves indirect ties. Then, the probability for a node to get infected rises with the number of adjacent nodes. In the same vein, the degree centrality is seen by Freeman, (1978) as index of potential communication activity. Then, the individual who holds a central position is more likely to transmit and receive knowledge flows.

We consider the evolution over time fo the average centrality degree by calculating the measure for each moving window t-1 t-5.

Definition of technologically specialized and academic inventors

We distinguish the average level of degree centrality (within and across region) for specific sets of nodes that are expected to contribute more to the innovations in MedTech sector. We characterize the inventors according to their technological specialization. In order to do so, we classify inventors according to their history in terms of inventions by analyzing their stocks of patents. We classify the inventors in three groups: inventors specialized in MedTech technologies (or MedTech inventors),

[15] An example of serial duplication is the gossip: a private story can be in several places at the same moment and it does not usually pass by the same link twice, even if can pass by the same node several times. The typical example for parallel duplication process flow is the sending an email message to warn about an electronic virus. One person can send an email to many different other individuals at the same time, and it is not excludable that he will receive the same email back after some time.

inventors specialized in MedTech related technologies (or MedTech related inventors), and inventors specialized in other technologies.

We define a MedTech inventor in year *t* an inventor which has at least one MedTech patent during the time span *t-1 t-5*. We define an inventor as specialized in MedTech related technologies an inventors which has at least one patent in a technology that might be recombined with other technologie to generate MedTech patents. Finally the residual set of inventors are classified as inventors specialized in other technologies.

Our definition MedTech related tehcnologies is based on the analysis of backward citations of the MedTech patents. We consider the backward citations of MedTech patents during the time span *t-1 t-5*. Then, we consider the IPC classes of the patents cited by the MedTech patents at least once as the technologies that recombined have generated MedTech innovation. We define as MedTech related technologies all these IPC classes. The most cited MedTech related technologies are: measurement, instruments, Pharmaceuticals, Chemical engineering, machine tools and other special machines. Not surprisingly, many of these technologies are those in which Switzerland is historically specialized.

Finally, we identify the academic inventors. In order to do so, we collect all the names of the authors who have published at least one scientific article reporting an affiliation to a Swiss university. Then, we merge names of academics with the names of inventors in order to identify the academic inventors. We consider the academic affiliated to departments which might contribute to the development of MedTech sector such as engineering, chemistry, biology and medicine.

Regression Variables

In our analysis we consider as proxy of the innovative activity of the region in the MedTech sector the count of patent applications at EPO classified as MedTech. This variable will be our dependent variable in the regression exercise.

We consider three explanatory variables which measure respectively the degree centrality of inventors specialized in MedTech, the centrality of inventors specialized in MedTech related technologies and the centrality of the academic inventors.

Degree centrality measures the number of nodes to which the focal node is connected (Nieminen 1974). The main drawback of degree centrality is that it is proportional to the size of the network: the higher the number of nodes the higher the probability for an individual to generate connections. This might imply difficulties in comparing centrality values of networks of different size. We correct for the network size as suggested in Freeman (1978), see equation 1.

$$C_g(p_k) = \frac{\sum_{i=1}^{g} a(p_i, p_k)}{n-1}$$

Equation 1

Where $a(p_{i,} p_k)$ equals 1 if the inventors p_i and p_k are co-inventors; *g* is the subset of inventors for which we want to calculate the centrality degree (eg. MedTech inventors) ; n is the number of inventors (nodes) in the regional network.

We interpret $C_g(p_k)$ as the count of actual co-inventorships ties of inventor p_k over all the possible co-inventorships ties or equally, as the share of actual ties over the possible ties.

In equation 2 we normalize the index at regional level. We calculate the average centrality for the specialized inventors (MedTech) and we normalize it according to the centrality of the average inventor within the region. When $\text{Normalized}\, C_g(p_k)$ is larger than 1 it means that MedTech inventors (MT) are more central than the average inventor in the region and vice versa: the higher the Normalized C the higher the connectedness of MedTech inventors compared to the average inventor.

$$\text{Normalized}\, C_g(p_k) = \frac{\sum_{k=1}^{n.MT} C_{n.MT}(p_k)}{n.MT} \Bigg/ \frac{\sum_{k=1}^{n} C_n(p_k)}{n}$$

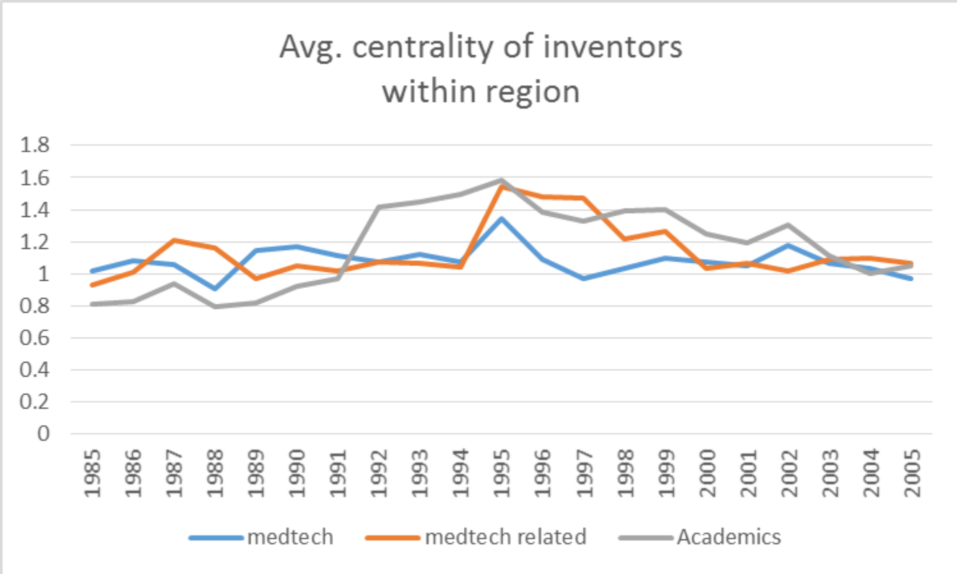
Equation 2

We define accordingly the degree centrality of inventors specialized in MedTech related technologies and the degree centrality of academic inventors.

Similarly we measure the cross-border regional ties of MedTech inventors by counting the inventors' connections to other Swiss inventors outside the focal region. We then correct for the number of possible connections to Swiss inventors located in other regions (as in equation 1) and finally we normalize according to the number of cross-border ties of the average inventor in the focal region (as in equation 2).

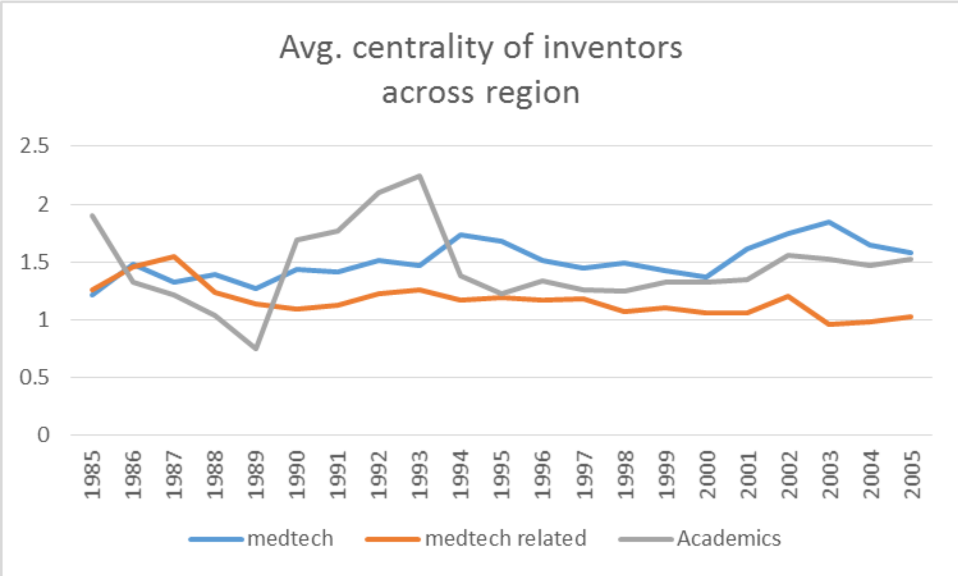
Figure 2 and 3 show the average normalized degree centrality within and across region for the three categories of inventors (MedTech, MedTech related, and academics).

Figure 2: Within region centrality



Avg. centrality of inventors within region
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
1985
1986
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
medtech
medtech related
Academics

Figure 3: Across region centrality



We include in the econometric exercise a list of control variables. We control for the number of inventors in year t, for the concentration of innovative activity within the region (Herfindhal index based on the shares of the patent applicants) and for the technological specialization of the region (Herfindhal index based on the share of patent technologies).

The two concentration indexes are calculated during the five year window from t-1 to t-5. The applicant *j* is assigned to a region *i* according to its address reported in the patent document. A high value of the index means that few applicants own the largest share of patents in the region *i*. To what concern the concentration index of the technologies we consider the share of patents classified in each technology class during the five year time window. The patents are assigned to a region *i* according to the inventor address reported in the patent document. A high value of the index means that few technologies lead the largest share of patents. Finally, we control for unobserved time invariant characteristics of the region with fixed effects and for time trends with year dummies. Table 2 shows descriptive statistics for all the variables.

Table 2: Descriptive statistics

Variables	Obs	Mean	Std. Dev.	Min	Max
log(1+count medtech patents)	546	1.77	1.31	0.00	5.15
log(1+count not medtech patents)	546	3.90	1.38	0.00	6.79
log(1+Centrality medtech inv.)	546	0.43	0.41	0.00	2.01
log(1+Centrality medtech rel. inv.)	546	0.45	0.40	0.00	2.22
log(1+Centrality medtech academic inv.)	546	0.20	0.37	0.00	1.76
log(1+Centrality medtech inv. spill)	546	0.70	0.45	0.00	2.07
log(1+Centrality medtech rel inv. spill)	546	0.48	0.39	0.00	1.73
log(1+Centrality medtech academic inv. spill)	546	0.26	0.43	0.00	2.22
H index technology	546	0.01	0.02	0.00	0.33
H index applicants	546	0.08	0.10	0.01	1.00
log(1+n. of inventors in t)	546	4.17	1.67	0.00	7.73

4. **Results**

Table 3 shows the results of the regression exercise[22]. The degree centrality of inventors specialized in MedTech impacts positively on the probability of generating MedTech innovation at regional level: 1% more centrality of MedTech inventors augment by 0.39% the number of MedTech patents. Similarly, an increase of 1% of centrality of inventors that are specialized in MedTech related technologies, increases by 0.29% the number of MedTech patents (column 1). Finally, centrality of academics impacts positively on the level of innovation in MedTech although the coefficient is not significant.

Table 3: regression table.

VARIABLES log(1+...)	(1) count MedTech patents	(2) count not MedTech patents	(3) count MedTech (dynamic)	(4) count not MedTech (dynamic)
Dynamic model				
L.count (not) medtech			0.25***	0.00059
Degree cenrality within region				
Centrality medtech inv.	0.33***	-0.030	0.19**	-0.0034
Centrality medtech rel inv.	0.29***	-0.020	0.21**	-0.026
Centrality medtech academic inv.	0.048	0.13	0.064	0.040
Degree centrality across region				
Centrality medtech inv. across region	-0.11	-0.027	-0.092	-0.028
Centrality medtech rel inv. across region	-0.20*	-0.025	-0.19*	-0.032
Centrality medtech acad. inv. across region	0.11	0.034	0.10	0.066
Controls				
H index technology (no log)	3.54**	-3.16***	0.43	-4.34***
H index applicants (no log)	0.29	-0.065	-0.21	0.32
n. of inventors in t	-0.073	0.15***	-0.039	0.12***
Year dummies	*yes*	*yes*	*yes*	*yes*
Regional fixed effects	*yes*	*yes*	*yes*	*yes*
Constant	1.11***	3.01***	0.93***	3.00***
Observations	546	546	520	520
R-squared	0.442	0.578	0.469	0.570
Number of regions	26	26	26	26

In order to show that the impact of the centrality of specialized inventors does not affect the innovation in non-MedTech sector, we run a counterfactual regression exercise where the dependent variable is the number of patents in non-MedTech sectors (see column 2). As expected, we find no impact of the centrality of inventors specialized in MedTech.

The impact of the inventors' centrality within the region seems to be predominant for innovation in MedTech sector: what matters in fostering MedTech innovation is the centrality among the inventors physically close and belonging to the same industrial cluster. This is confirmed by the fact that we do not find any impact of the level of centrality of inventors across region, except for a barely significant

[22] We use an OLS estimator with fixed-effect. One of the assumptions of linear regression model is homoscedasticity and normally distribution of error terms. This assumption is violated with count variables so we apply the logarithm functional form to all the dependent and independent variables: log(1+VARIABLE). A model with a log dependent variable satisfies better the OLS assumptions (Wooldridge, J. 2012). This transformation allows to interpret estimated coefficients as elasticities. All the dependent and independent variables are in log(1+…) except the dummies and the H indexes.

negative impact of the centrality of MedTech related inventors (Column 1). As expected centrality of specialized inventors do not impact on non-MedTech innovation across region (Column 2).

The technological specialization of the region (H technology) has a positive impact on the innovation in MedTech sector, while negative on the innovation in non-MedTech sectors: the higher the technological specialization of the region the higher the number of MedTech patents. The same applies to concentration in terms of patent applicants at regional level, although not significantly.

We run a robustness check by including as control the number of MedTech inventors during the years t-1 to t-5. The results on centrality degree are confirmed. We also run a regression restricting to a sub-sample including only region-year pairs where the dependent variable is strictly larger than zero. Results are confirmed as well. Columns 3 and 4 are dynamic specifications of the models presented in columns 1 and 2. Our results are robust also to this specification. In table 4 in appendix concentration index are interacted with the centrality measures.

5 Conclusions

The paper assess the impact of the structural properties of the network of inventors on the innovative performance of the regions. We focus on the Swiss medical device sector. We measure the structural characteristics of the network taking into account the technological heterogeneity of the inventors and their academic status. We consider two separate networks: the one accounting for the co-inventorship relation within the region and the one accounting for the co-inventorship relations across the region. We find that only the structural properties of the network within region impact on its innovative performance in the MedTech sector. Moreover, we find that centrality of inventors specialized in MedTech or MedTech related technologies impact positively on the innovative performance. Surprisingly centrality of academic inventors do not foster innovation, although MedTech technology was expected to benefit from the presence of highly connected academic inventors.

LIMITATIONS

It could be interesting to look not just at the regional level but also at the language level: in other words it could be interesting to see how the network structure evolves across the regions where the same language is spoken. Moreover, due to the small dimension of Switzerland, it will be more interesting to group those regions that have different NUTS3 but that are actually the same region and divide the ones that have inside them natural barriers like mountains.

Another limitation is related to the definition of medical device sector. Medtech has 16 subgroups, according to the definition of the Global Medical Devices Nomendature (GMDN) Agency[23]. Some of them are more technological advanced than others and they need very different knowledge to develop new technologies. In our work we decide to keep the definition of medical device sector as a unique sector, without making difference between the different subfields, and consequently, to the previous knowledge needed. It would be interesting to analyze the subgroups to define better the technologies related to all of them.
The last limitation regards the use of patent data. We agree on the fact that these kinds of data cannot cover the entire possible connections among actors. The best would be to prepare a survey to undergo to surgeons, professors, and firms in order to understand which the most used channels of connections are and how much we are underestimating this phenomenon. We leave this extension as a possible continuation of this work.

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[23] The subclasses are: Active implantable devices, Anesthetic and respiratory devices, Dental devices, Electromechanical medical devices, Hospital hardware, In vitro diagnostic devices, Non-active implantable devices, Ophthalmic and optical devices, Reusable devices, Single use devices, Assistive products for persons with disability, Diagnostic and therapeutic radiation devices, Complementary therapy devices, Biological-derived devices, Healthcare facility products and adaptations, Laboratory equipment

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APPENDIX

Table 4: regression analysis with interactions between industry concentration and centrality of inventors. All the dependent and independent variables are in log(1+…) except the dummies and the H indexes.

VARIABLES	(1) count MedTech patents	(2) count not MedTech patents	(3) count MedTech (dynamic)	(4) count not MedTech (dynamic)
Dynamic model				
L.count (not) medt			0.23***	0.00069*
Degree cenrality within region				
Centrality medtech inv.	0.57***	-0.10	0.39***	-0.061
Centrality medtech rel inv.	0.56***	0.15*	0.36**	0.16*
Centrality medtech acad inv.	0.075	-0.15	0.15	-0.19
Degree centrality across region				
Centrality medtech inv. across region	-0.11	-0.033	-0.095	-0.028
Centrality medtech rel inv. across region	-0.19*	-0.039	-0.18*	-0.042
Centrality medtech acad inv. across region	0.090	0.0073	0.11	0.030
H index technology (no log)	2.79*	-3.10***	0.82	-4.51***
H index applicants (no log)	0.78*	-0.10	0.50	0.36
n. of inventors in t	-0.082	0.14***	-0.053	0.11**
Interactions				
H applicants X Cent inv.	-2.25**	1.17**	-2.34**	0.89
H applicants X Cent rel inv.	-2.02**	-1.30**	-0.98	-1.42***
H applicants X Cent acad inv.	0.82	2.37*	-0.63	1.96
H tech X Cent inv	-11.9	0.37	-1.30	1.72
H tech X Cent rel inv.	-22.1	-12.2	-16.7	-11.8
H tech X Cent academic inv.	-78.3	83.6**	-71.6	73.4
Year dummies	*yes*	*yes*	*yes*	*yes*
Regional fixed effects	*yes*	*yes*	*yes*	*yes*
Constant	1.15***	3.02***	0.88***	3.01***
Observations	546	546	520	520
R-squared	0.464	0.590	0.480	0.581
Number of regions	26	26	26	26