How to Foster Innovation? Unpacking Workforce Skills Composition

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Aim

Many theoretical strands have widely recognised the importance of innovation for economic growth and aspire to learn the antecedents of companies' decision to invest in innovation at different levels (Thompson, 2018; Pradhan et al. 2018). Within this field of studies, innovation is conceived as the keystone for the development of an increasingly competitive and dynamic knowledge-based economy (European Commission, 2009).

A high content of creative work and know-how will be able to guarantee the future competitiveness of companies and act as a driving force for the entire economy. Knowledge-intensity activities are, in fact, essential to stimulate employment absorption and to help the transition of traditional business sectors to new sectors with still unexplored potential (Papanastassiou et al., 2020). The innovative capacity strongly depends on knowledge as well as on human, structural and relational capital (Mariz-Pérez et al., 2012). Human capital mainly concerns the composition of the skills of the workforce that directly participate in knowledge-generation activities. Their relationship with innovation is still blurred, in the sense that the role that skills have on innovation is not yet universally clear.

It follows that the determinants of innovation differ in importance, depending on the circumstances and making their identification complex. An increasing number of researchers have over the past two decades aimed to identify the factors that encourage or hinder firms in developing and adopting innovation. However, the majority of these studies mainly focus on innovation at the company level, while neglecting their territorial dimension. To the best of our knowledge, no investigation has so far considered in depth the real propensity of a territory to innovate and only a small body of literature has provided a comprehensive framework for investigating the explanatory variables of innovations from a territorial perspective.

The osmotic process of skills, attitudes and intellectual agility, and the 'knowledge networks' that develops thanks to the mobility of workers between companies inevitably affect the productive structure of a territory (Stoyanov and Zubanov, 2012). As with all investments aimed at increasing the future competitiveness of a company, the engine of the development of a territory can only pass through the implementation of innovations.

This work aims to explore the main determinants that favour the capability of a territory to generate and disseminate innovation and the reasons for their possible changes over time (e.g. from low to high level of innovation intensity), considering the geographical concentration of innovative agents, the human capital heritage and labour mobility. Specifically, this contribution will be focused on the Italian provinces, given the current shortage of studies on their adaptive innovation-related skills. The provinces in Italy represent such a geographical detail that they can be considered quite differentiated from each other. Each province is usually characterised by their own productive specialisations and human capital endowments, which represent a strategic factor for economic development (Gumbau-Albert and Maudos, 2009).

The high level of territorial detail allows us to capture patterns of spatial heterogeneity that would remain hidden at a more aggregate level. Italy is an interesting case study as its historical North-South economic divide also reflects in innovation outcomes and human capital accumulation. The study provides guidelines both for policymakers who plan to incentivise innovation and development of territories and for entrepreneurs/managers who aim to understand the factors that could stimulate or guide their companies to make innovations.

2. **Method and data**

We performed panel data regression models (Greene, 2000) to follow the dynamics of innovation intensity over time. In particular, the ordered probit panel data models with random effects (Butler and Moffitt, 1982; Greene, 2000) allowed us to manage time-invariant regressors and to control for potentially correlated heterogeneity. The aim was to assess how specific factors affect the probability for each province to move among different levels of innovation intensity.

Formally:

(1)

is the variable linked to the ordinal categories of the dependent variable , which measures provinces' innovation capacity by the following measurement model:

(2)

where m identifies the three categories (1: *low*; 2: *middle;* 3: *high*) and the thresholds to be estimated (along with the β coefficients) in order to differentiate the levels of innovation activities. Moreover, x_{it} is the $1 \times k$ vector of covariates, and α_i is the time-constant, individual-specific effect, which is composed of two parts: the first (α) is constant and independent from *i* and *t* and the second (ν_i), the unit-specific residual, is random and differs among units. α_i, also named unobserved heterogeneity, captures time-invariant unobservable effects. ε_{it} is the disturbance term with zero mean, homoscedastic, not autocorrelated and uncorrelated with regressors and ν.

A further assumption is the strict exogeneity, which allows the estimation of time-invariant regressors (e.g., population density), and uncorrelation between the individual effects α_i and the observed covariates. Exogeneity means orthogonality between individual effects (α_i) and observed covariates (x_{it}), that is, all regressors are assumed exogenous. Individual effects (α_i) are treated as a random variable that adds to error terms ε_{it}.

Data were taken from official sources – the European Patent Register (EPR) and Italian National Institute of Statistics (ISTAT) – for the period 2008-2015. The units of analysis are the Italian provinces (NUTS-3 level), which is the finest territorial level with information on patents intensity and covariates.

The dependent variable was built on patents intensity (i.e. ratio of the number of patents over the number of inhabitants), which is a good proxy of innovation activities (see, for example, Meliciani, 2000; Moreno et al., 2005). We categorised patents intensity as shown in eq. 2 (i.e., 1: low innovation intensity; 2: medium; 3: high).

Explicative variables concern three main macro-areas, i.e., demographic, economic, and skills' characteristics. Their selection was strongly based on the dominant literature in this field, while considering the constraints related to the data availability at such a high level of geographic resolution. We used: 1) *population density*; 2) *R&D expenditure as a percentage of GDP*; 3) *skills complementarity (skills overlapped, skills connected, and skills unlinked).* In particular, the skills complementary variables were defined following Neffke et al. (2017).

Table 1 shows details on all selected variables, which could help explain the innovation activities in Italy, their patterns, dynamics and determinants, also including references to the relevant literature and their expected relationship with the intensity patents.

Table 1: List of explanatory variables

Dimensions	Variables	Description	Expectation	References
Demographic	Population Density	Ratio between the total population and the total square kilometres of the municipality	*Positive:* in more urbanised areas, the innovative activities are higher	*Moreno et al. (2005)*
Economic	R&D expenditure as a percentage of GDP	Share of GDP devoted to the development of technological innovations and new products. It is relativised by the number of employees in R&D	*Positive:* R&D is an input to the generation of patents	*Sun et al. (2020); Gumbau-Albert and Maudos (2009); Meliciani (2000)*

Skills complementarity	Skills overlapped	New workers feature the same skills of those already existent in the province	*Ambiguous: it is strongly depends on the territorial origin of the worker*	*Cappelli et al. (2019)*
	Skill connected	New workers feature skills related (not the same) to existing ones	*Positive: it increases the capability of creating knowledge network*	*Neffke et al. (2017)*
	Skill unlinked	New workers feature skills unrelated to existing ones	*Negative: the process of acquiring or generating new knowledge is difficult*	*Cappelli et al. (2019)*

3. **Results**

This section covers the results of the two-step analysis: the transition probabilities matrix (TPM) and the ordered probit model with random effects. The TPM allows us to estimate the probability of staying in a state of innovation intensity status and the probability of moving from one state to another in a given period of time. We have three states: low innovation intensity (LII), medium innovation intensity (MII), and high innovation intensity (HII). The values on the main diagonal of the TPM represent persistence patterns, as they show the probability of remaining in the same condition during the specified unit of time. The adopted TMP framework includes six transition probabilities and three permanent states. In particular, we analyse the transitions between LII and MII, between LII and HII, between MII and HII, and persistence in these states.

Table 2 shows the transition probabilities for the years 2008-2015. In eight years, most of the provinces have maintained their early-term status. The probability that provinces with a low innovation intensity confirm their condition at the end of the period is 87%. A similar probability (85.29%) confirms a high innovation intensity, while the probability of persisting in the medium state is lower (72.32%). As can be expected, the medium status presents the most interesting results in terms of transition probabilities because provinces could move towards lower innovation intensity levels as well as higher levels with very similar probabilities. In fact, provinces appear to have almost the same probability of worsening their innovation intensity (15.5%) and improving their innovation outcomes (12.18%). However, some differences emerge. A province in the medium state is more likely to regress to the low state rather than improve its ranking. This is an interesting result because it highlights how difficult is for the midway provinces to take a step forward by improving their innovation outputs.

Another point of interest is the transition of low innovation intensity (LII) provinces because these provinces can simple move towards the medium level (with a probability of 13.06%). In other words, in the years under consideration, it seems impossible to reach the level of high innovation intensity (HII) outcome level whether the province belongs to LII. Finally, the probability of regressing from HII to medium innovation intensity (MII) is equal to 14.34%, a non-negligible value.

In summary, by comparing the different transition probabilities, we can outline the following considerations: *i*) the provinces of the MII group are more likely to move to the LII group rather than to the HII group; *ii*) the provinces in LII cannot reach the HII group; *iii*) the probability of moving from HII to MII is greater than that of moving from LII to MII. In other words, a good performer is more likely to worsen his condition than a low performer will improve its condition; *iv*) considering all the possibility of transition, the probability of worsening (bottom diagonal of matrix) the condition is greater than the probability of improving it (upper diagonal of matrix).

Table 2. Innovation intensity transition matrix, 2008-2015

t/(t+1)	**LII**	**MII**	**HII**	**Total**[a]
LII	213 (86.94)	32 (13.06)	0 (0)	245
MII	42 (15.50)	196 (72.32)	33 (12.18)	271
HII	1 (0.37)	39 (14.34)	232 (85.29)	272
Total[b]	256 (32.49)	267 (33.88)	265 (33.63)	788

Note: ([a]) longitudinal population by innovation intensity status at the beginning of the period. ([b]) longitudinal population by innovation intensity status at the end of the period. Transition probabilities in ().

Although valuable, the information obtained through the TPM is partial as it only allows us to explore the probability to state changes, but nothing is known about what factors drive these changes and what their impact on innovation is. To this end, a second step of analysis is based on the ordered probit model with random effects, using the low level of innovation intensity as the reference category **(Table 3)**.

Table 3. Estimation results of the ordered probit model with random effects, 2008-2015

	Coefficient
Population density	0.001 (0.0009) *

R&D	2.013 (0.489) ***
Skills overlapped	0.015 (0.020)
Skills connected	0.079 (0.028) ***
Skills unlinked	-0.222 (0.076) ***
Cut 1	3.322 (2.585) *
Cut 2	6.127 (2.591)***
	6.381 (1.555)***
N	788

*Note: ***; **; *: Significance level at 1%, 5%, 10%.*

The resources devoted to R&D represent one of the main drivers of productivity growth and technical change in high knowledge-based sectors. Meliciani (2000) stated that these findings are particularly true when the analysis is carried out at the aggregate level. Our results show that *R&D* directly increases the probability of improving the state of innovation intensity, in line with the literature that has shown the decisive role of R&D in the development of patents in the USA (Anselin et al., 1997) and in Europe (Bottazzi and Peri, 2003). *Population density* is slightly significant (at 10%). Since this variable captures the role played by urbanisation – i.e. there may be a higher level of innovative activity in large metropolitan areas than in smaller ones due to agglomeration economies (Moreno et al., 2005) – we conclude that it does not play a key role in stimulating innovative activities.

The estimated coefficients of the skills complementarity variables (i.e., skills unlinked, skills connected, and skills overlapped) show the expected signs. The results highlight the null contribute of workers featuring overlapped skills in improving the probability of growth in local innovation capability. One possible explanation for the negligible impact of this type of skills is the lock-in effect. That is, workers with the same skills (of the ones already present in the provices) are unable to create new knowledge because the provinces are closed in on themselves, becoming isolated and impermeable, and preventing knowledge and fresh innovative ideas from the outside from flowing in (Cappelli et al., 2019). Workers with *skills connected* increase the probability of provinces to improve their innovation outcomes. This result confirms the pivotal role played by the complementarity of skills, highlighting how workers with connected skills are the most important type of human capital because cognitive proximity allows for the generation of new knowledge (Neffke et al., 2017). Regarding the *skills unlinked* variable, these workers are even detrimental to the provinces' ability to generate innovation. These workers, in fact, have experience in very different sectors than the most innovative ones and their skills are not absorbed in the context of high knowledge (Noteboom, 2000, Fitjar and Timmermans (2017). Consequently, workers with unlinked skills do not represent a real learning opportunity for other workers and cannot generate new knowledge.

4. **Implications**

The empirical results highlight two main aspects: *i)* to invest in innovative activities by increasing the R&D budget; *ii)* to pursue skills-complementarity valorisation. Local governments as well as business managers should aim to activate a skills flow process through knowledge networks, avoiding the excessive specialisation of these networks. This is because the concentration of workers with the same skills (i.e. skills overlapped) does not seem to increase the innovation intensity of the provinces.

A possible action could be the adoption of network contracts between companies (but also universities, spin-offs, research centers, etc.) belonging to the same knowledge chain but specialised in different stages of innovation production (e.g., contracts between firms of the same vertical production chain). In Italy, network contracts are regulated by LAW 33/2009, but their adoption is rather poor. They are stipulated by several firms with the aim of increasing, individually and collectively, the innovative capacity and competitiveness on the market. To this end, the companies undertake to collaborate on the basis of a common program, exchanging information or services of an industrial, commercial, technical or technological nature and jointly carrying out one or more activities. To improve the adoption of this type of collaboration, it may be appropriate to bring together workers with connected skills (avoiding, on the one hand, excessive overlapping of skills and, on the other one, by combining people with heterogeneous knowledge endowments).

References

Anselin, L., Varga, A., Acs, Z. (1997). Local geographic spillovers between university research and high technology innovations. *Journal of urban economics*, *42*(3), 422-448.

Bottazzi, L., Peri, G. (2003). Innovation and spillovers in regions: Evidence from European patent data. *European Economic Review* 47(4), 687-710.

Butler, J.S., Moffitt, R. (1982). A computationally efficient quadrature procedure for the onefactor multinomial probit model, *Econometrica* 50 (3), 761-64.

Cappelli, R., Boschma, R., Weterings, A. (2019). Labour mobility, skill-relatedness and new plant survival across different development stages of an industry. *Environment and Planning*

A: Economy and Space 51(4), 869-890.

European Commission (2009). Communication from the Commission to the Council, the European Parliament, the European Economic and Social Committee, and the Committee of the Regions: A Mid-Term Assessment of Implementing the EC Biodiversity Action Plan. *Journal of International Wildlife Law & Policy* 12(1-2), 108-120.

Fitjar, R. D., Timmermans, B. (2017). Regional skill relatedness: towards a new measure of regional related diversification. *European Planning Studies* 25(3), 516-538.

Greene, W.H. (2000). Econometric analysis 4th edition. *International edition, New Jersey: Prentice Hall*, 201-215.

Gumbau-Albert, M., Maudos, J. (2009). Patents, technological inputs and spillovers among regions. *Applied Economics* 41(12), 1473-1486.

Mariz-Pérez, R. M., Teijeiro-Álvarez, M.M., García-Álvarez, M.T. (2012). The relevance of human capital as a driver for innovation. *Cuadernos de economía* 35(98), 68-76.

Meliciani, V. (2000). The relationship between R&D, investment and patents: a panel data analysis. *Applied Economics* 32(11), 1429-1437.

Moreno, R., Paci, R., Usai, S. (2005). Spatial spillovers and innovation activity in European regions. *Environment and planning A*, *37*(10), 1793-1812.

Neffke, F., Otto, A., Weyh, A. (2017). *Skill-relatedness matrices for Germany: Data method and access* (201704_en). Institute for Employment Research, Nuremberg, Germany.

Nooteboom, B. (2000). *Learning and innovation in organizations and economies*. OUP Oxford.

Papanastassiou, M., Pearce, R., Zanfei, A. (2020). Changing perspectives on the internationalization of R&D and innovation by multinational enterprises: A review of the literature. *Journal of International Business Studies* 51(4), 623-664.

Pradhan, R. P., Arvin, M.B., Bahmani, S. (2018). Are innovation and financial development causative factors in economic growth? Evidence from a panel granger causality test. *Technological Forecasting and Social Change* 132, 130-142.

Stoyanov, A., Zubanov, N. (2012). Productivity spillovers across firms through worker mobility. *American Economic Journal: Applied Economics* 4(2), 168-98.

Sun, X., Li, H., Ghosal, V. (2020). Firm-level human capital and innovation: evidence from China. *China Economic Review* 59, 101388.

Thompson, M. (2018). Social capital, innovation and economic growth. *Journal of Behavioral and Experimental Economics* 73, 46-52.