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Abstract
The development of the technological space of a manufacturing region relates to its human capital. However, the dynamic relation between local firms' workforce composition and their adoption of Industry 4.0 enabling technologies over time is still under investigated. The paper contributes to filling this gap analysing the relation over 10 years between technology adoption and the occupational choices of 1800 firms from one of the most industrialized regions of Italy: the Veneto Region. The results from descriptive as well as inferential analysis show that such relational dynamics are a multifaceted phenomenon, presenting a series of counterintuitive features.

Keywords
Digital technologies, Industry 4.0; manufacturing region, workforce, SME

JEL Codes
R11,O33, E24

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The Evolution of Technological Space and Firms' Workforce Composition in a Manufacturing Region

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The Evolution of Technological Space and Firms' Workforce Composition in a Manufacturing Region

ABSTRACT

The development of the technological space of a manufacturing region relates to its human capital. However, the dynamic relation between local firms' workforce composition and their adoption of Industry 4.0 enabling technologies over time is still under investigated. The paper contributes to filling this gap analysing the relation over 10 years between technology adoption and the occupational choices of 1800 firms from one of the most industrialized regions of Italy: the Veneto Region. The results from descriptive as well as inferential analysis show that such relational dynamics are a multifaceted phenomenon, presenting a series of counterintuitive features.

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INTRODUCTION

Several contributions in innovation studies and evolutionary economic geography clearly highlight the role of path dependency in regional technological trajectories (Frenken, Van Oort, & Verburg, 2007; Neffke, Henning, & Boschma, 2011). Disruptive challenges along such trajectories, such as the adoption of Industry 4.0 enabling technologies (Büchi et al., p. 4), may become positive for a region if the potential offered by the digital transformation is absorbed within the territorial context (De Propris & Bailey, 2020). Structural and institutional characteristics of the regional system shape the absorption of the technological potential (Grillitsch, Asheim & Trippl, 2018; Isaksen & Trippl, 2016). In this, the role played by the local industrial structure is key (Chaminade, Bellandi, Plechero & Santini, 2019; Teece, 1996). The evolution of the technological space depends quite substantially on the local firms' repository of competences, and on the capacity of firms characterizing the embedded regional structure to employ a highly qualified workforce that is committed to learning new processes and therefore able to cope with the incoming new knowledge (Boshma, 2013, Krzywdzinski, 2017).

In regions that are still characterized by an intensive traditional manufacturing specialization and a dense population of small and medium enterprises (SMEs), new digital technologies may however become a threat rather than an opportunity for regional development. Cognitive lock-in faced by local firms when trying to renew their embedded competences often represents one of the main obstacles (Grabher, 1993; MacKinnon, Cumbers, & Chapman, 2002; Martin & Sunley, 2006). The injection of competences from a new knowledge basis in the regional industrial structure could represent a way of turning disruptive challenges, such as those brought about by Industry 4.0, into a positive shock (Bellandi, Chaminade & Plechero, 2020). However, the dynamic relation between firms' technological adoptions and the changes in skills of firms' human resources still needs to be properly addressed.

Understanding how the evolution of the technological space of a region goes hand in hand with the evolution of the local firms' human resources is crucial in order to answer one important question: *How* *do local firms within a traditional and industrialized region adapt their workforce composition in terms of specialists to cope with the disruptive adoption of Industry 4.0 technologies over time?*

This aspect will be investigated using as a case study the Veneto Region, one of the most industrialized regions of Italy with a strong manufacturing specialization, particularly in traditional low and medium tech industrial sectors, such as fashion and furniture, as well as mechanical and electrical machine-tools. We will do so by using a unique and integrated database created by a Regional Observatory of the local economy, which has recently enlarged its membership to include several local stakeholders and official data providers.

Our analysis focuses first on the evolution of the technological space of the region over time. To represent such a space, we consider each digital technology a node, and their co-adoptions in a certain year as a tie. The resulting network shows that digital technologies are gradually adopted and co-adopted by the sample firms, but that a clear structure, centred on a 'backbone' composed of initially two, and later on four, technologies clearly emerges.

We also investigate the co-evolution of local firms' digital technology adoption and occupational choices in terms of specialized workers, either *technicians*, whose knowledge has a synthetic nature, or *scientific specialists* possessing analytical knowledge (according to the definition by Asheim & Coenen, 2005). However, such co-evolution presents a series of unexpected features. The descriptive analysis shows that, while firms that adopted at least one technology in the observation period employ more specialized workers than non-adopters, they do not seem to increase such a workforce more than non-adopters over time, and this occurs despite the fact that they do adopt a series of new digital technologies in that time window. Occupational choices and digitalization seem *not* to co-evolve over time.

The regression analysis allows us to dig deeper into this effect showing that this surprising aggregate result is likely due to the heterogeneity of the effects of the different technologies. While Artificial

Intelligence seems to be a substitute for specialists of any kind, Additive Manufacturing complements specialists' work, especially when they carry synthetic knowledge (technicians). Automation & Robotics, however, relate in a very different manner to different groups of specialists: they enhance the work of technicians, but divert attention (and thus investments) from scientific specialists. All in all, our results provide a vivid picture of the complex relations that tie together workforce competences and digital transformation in a traditional and industrialized region, suggesting that a multifaceted approach should be used to study Industry 4.0.

The paper is organized as follows: the next section illustrates the theoretical background, providing insights regarding the relation between the technological space of a region and firms' micro conditions. We discuss in particular the key occupational profiles supporting the integration of digital technologies. The method section provides information about the type of data used and the type of analysis that has been conducted. After presenting the description of the technological space of the Veneto Region and its evolution through time, we illustrate the results of the econometric analysis. We show how the adoption of digital technologies relates to two specific profiles of the workforce: technicians and scientific specialists. The following section discusses the results, providing reflections on how occupational dynamics is impacted by the incoming new knowledge. The last section concludes by highlighting some policy implications.

BACKGROUND

Digital technologies and regional development in a manufacturing region: the role of micro conditions

When considering the relation between regional development and technological change the role of human capital in firms and related competences should be carefully addressed as one of the micro aspects of innovation that most influence regional renewal (Boschma, R., Iammarino, S. & Steinmueller, E., 2013; Fritsch, Kudic & Pyka, 2019). Castellacci, Consoli, & Santoalha (2019) use occupational data to analyse different profiles related to e-skills within European regions. The authors show that nowadays in European regions those skills are crucial to supporting new paths of regional diversification. Disruptive challenges such as those brought about by the last generation of digital technologies may lead to problems of skill mismatch in local firms, and this in turn may stop or cause a drift towards a negative dynamics in the evolution of regional innovation processes. This may happen when the qualifications of employees in the local industrial structure do not reach the level required to cope with new Industry 4.0 enabling technologies (Brynjolfsson & McAffee, 2014). In traditional sectors like those under scrutiny here this may happen in many firms. Moreover, the regional labour market might show certain rigidities when meeting technological change (Antonelli & Quatraro, 2013), impeding the adaptation of the workforce due to the relocation of workers with different backgrounds and qualifications.

As stressed by studies on labour and skills, processes of skill renewal in firms are strongly shaped by place contingencies (Filippetti, Frederick, & Iammarino 2019, p.219; Peck & Haughton,1991, p. 829). The well recognized limited adaptive nature of the SMEs typical of many traditional manufacturing regions in Italy may risk slowing down or shrinking the opportunities that technologies offer to support regional development (Bellandi et al., 2020). These regions may be more prone to reach the path exhaustion of their industrial specialization sooner if the organizational structure remains cognitively locked into previous knowledge-basis structures (Chaminade et al., 2019; Trippl & Isaksen, 2016).

As has happened in other countries, Italy has also experienced large-scale state investment to support Industry 4.0 particularly in manufacturing regions. The 2017 National Plan, for example, has provided a series of financial incentives to support firms' material and immaterial investments in industrial machinery and automation (Ministero dello Sviluppo Economico, 2018a). However, within firms the implementation of the plan has seen the lion's share of investment go to technological infrastructure, and has not been accompanied by an equivalent investment in human resources (Ministero dello Sviluppo Economico, 2018b). Indeed, the literature identifies the lack of firms' digital strategies to embrace change, and the under-qualified profiles of firms' employees as being the most pressing problems faced by local companies in realizing the full potential of Industry 4.0 (Geissbauer, Schrauf & Koch, 2014; Kiel, Arnold, & Voigt, 2017; Raj et al, 2019), particularly when considering SMEs (Corò & Volpe, 2020).

The knowledge-base profile of a firm's workforce

The type of knowledge-base profile of the local workforce may significantly influence the growth path of regional and local systems (Bellandi, Chaminade & Plechero, 2020; Grillitsch, Martin, & Srholec, 2017; Grillitsch, Schubert, & Srholec 2019).

In traditional manufacturing regions the operating processes of the workforce employed in firms is frequently related to what in literature is called the 'Doing, Using and Interacting (DUI) mode of learning' (Jensen, Johnson, Lorenz, & Lundvall, 2007). In Italian regions which traditionally have a large population of SMEs and where the Made in Italy identity is strong - such as the Veneto Region -, workers and the related semi-automatic learning mechanisms have represented for a long time an important support for developing local firms' competitive advantage based on niche production and flexible specialization (Becattini, 2001).

In the light of recent digital challenges, the mismatch between the above described embedded profiles of human resources and the new skills needed for the correct absorption of the technological potential emerged clearly (Brynjolfsson & McAffee, 2014).

The adoption of the latest-generation digital technologies often requires a more strategic governance and the full understanding of technology and of the science-based knowledge potentially applicable to production processes, organizational activities and logistics (Raj et al., 2019). However, activating Science, Technology and Innovation (STI) learning processes (Jensen et al., 2007) amongst the workforce may be difficult when employees lack high qualifications in their profiles. Activating only employees' usual training might not be enough to support a strong adaptation of traditional workers' profiles to the use of Industry 4.0 enabling digital technologies. Thus, firms may decide to change their workforce composition, and in particular to employ new specialized professional profiles.

The literature suggests that a co-existence between specialized workers supporting the correct use of technological artifacts and services (who possess the "know how") and workers in charge of understanding the rationale behind those artifacts and services, and the potential they could have for firms' innovation and growth (those who possess the 'know why') is desirable (Jensen, et al., 2007, 982; Nelson, 2004). Two workforce profiles seem therefore particularly key in accompanying firms' adoption of new technologies:

- *Employees with synthetic knowledge-basis profiles supporting know 'how'.* As stressed by Asheim & Coenen (2005) who originally applied the concepts, synthetic knowledge is originated by the application and new combination of existing knowledge, and it is aimed at solving specific problems. It is usually associated with the technical and engineering background and experience of employees. In particular, the presence of production technicians or technicians with an engineering background or with dedicated technical software knowledge would be desirable when new digital technologies are going to be adopted by firms.

- *Employees with analytic profiles supporting know 'why'.* Analytical knowledge is usually codified and characterized by scientific knowledge and rational processes, the application of experiment-based methods and scientific laws (Asheim & Coenen, 2005). As a pre-requisite, this knowledge base often requires a specialized knowledge of 'what' needs to be done (Jensen et al., 2007). The application of analytical knowledge to the production system can be therefore associated with the presence of scientific specialists within the firms. They might be specialized employees with an understanding of technological potential and choices. These profiles could support the firm in extracting value from the adoption of digital technologies.

Thus, with the adoption of new digital technologies in a manufacturing region we expect to see a corresponding change in the firms' workforce composition, and in particular an increase in the number of technicians and scientific specialists compared to the total number of employees. We expect also that the more sophisticated technologies of the latest generation will affect this process more than simple or common-use technologies.

DATA AND METHOD

In order to examine the dynamic relationship between the number of technicians and scientific specialists working in local firms and the firms' adoption of digital technologies in the region over time, we make use of a unique and recently integrated dataset created by a regional Observatory aimed at quantitatively mapping the adoption of digital technologies related to Industry 4.0[1]. The data originally collected by Unioncamere Veneto (the association of the seven Chambers of Commerce, Industry, Crafts and Agriculture of the Veneto Region) in 2019 cover a representative sample of 1807 firms[2]. The data have been integrated with sets of statistics from two other official sources: one provided by the Regional Labour Agency responsible for data relating to regional employment and the labour market (Veneto Lavoro), the other being the AIDA database – a dataset containing official

[1] The regional Observatory was constituted in 2020 by different local stakeholders (Unioncamere, Chamber of commerce of Treviso, Veneto Lavoro and The Ca' Foscari University of Venice) with the aim of integrating regional information at firm level and mapping the relation between new digital technologies, occupation data and firms' economic and financial performances.

[2] The sample is representative of the population in terms of firm size, type of production and sector. The representativeness has been ensured by Unioncamere Veneto in charge of periodic collection of official statistics that has taken the full responsibility for collecting the data about the firms' adoption of digital technologies and the year of their introduction. Firms having less than 10 employees have been excluded.

economic and financial information about limited companies[3].

Table 1 - Characteristics of sample firms

Firm's size		Typology of production		Manufacturing sector	
Small	81%	Capital goods	19.17%	1. Food. drinks and tobacco	7.28%
Medium	16.39%	Intermediate goods	47.61%	2. Textile. clothing and footwear	11.78%
Large	2.61%	Customer goods	33.22%	3. Wood and furniture	10.28%
				4. Paper and print	4.83%
				5. Rubber. plastic	8.22%
				6. Marble. glass. ceramic and other minerals	4.56%
				7. Production of metals and metal products	17.28%
				8. Mechanic machines and apparatus	12.28%
				9. Electrical and electronic machines	8.61%
				10. Means of transport	1.83%
				11. Goldsmith	1.72%
				12. Eyewear	1.67%
				13. Other manufacturing firms	9.67%
Total number of firms: 1800					

The dataset allows us to combine a variety of data sources at firm level for the period 2008-2018, such as typology and year of technological adoption, stock and variation of firms' workforce and cost of labour (see appendix A for a description of the variables used in the paper). For the purpose of this paper, we have analysed selected data through network analysis and econometric regression models.

The next section will illustrate the technological space of the Veneto Region and show some graphs about its evolution by means of the network analysis techniques. The sections that follows presents graphs illustrating the relation between labour dynamics and technology adoptions, the regression models, and the related results.

The evolution of the technological space in the Veneto Region: network analysis

The sample collected by Unioncamere Veneto in 2019 allows us to map the regional technological space explored by the main regional industrial structure, and in particular the firms' adoptions over

[3] The matching of the original sample with the Veneto Lavoro dataset has been possible in 1700 cases, while with the AIDA dataset for 1464 cases. Despite the fact when data are combined the sample is reduced in size, it has in both cases maintained a very similar composition in terms of firm size, type of production, and sector, ensuring the maintenance of its regional representativeness.

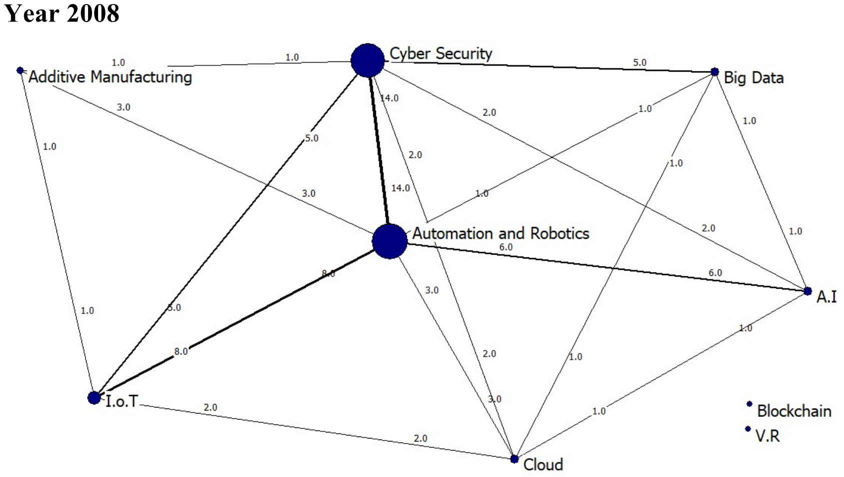
time in relation to 9 different digital technologies which nowadays are considered key pillars of Industry 4.0 (Büchi, Cugno, & Castagnoli, 2020; Brynjolfsson & McAffee, 2014): Artificial Intelligence (A.I), Automations and Robotics, Additive Manufacturing, Internet of Things (I.o.T), Virtual and Augmented Reality (V.R), Cloud Services, Cyber Security, Big Data Analytics, and Blockchain. A reasonably large number of firms (45%) adopted at least one of these technologies. However, only 11% of adopters have so far employed more than 3 technologies. This percentage seems to indicate that only around one out of ten firms have indeed put in place a sophisticated technological infrastructure. Most of the firms have invested in Automation & Robotics, which is clearly fundamental for local manufacturing industry in the region, and in Cyber Security, usually considered an important auxiliary technology, but not as central as other technologies for the improvement of firms' productive processes and the possible renewal of firms' business model.

By considering the 9 technologies as nodes and their co-adoption in one firm as a tie (so that the strength of the tie is given by the number of firms in which such co-adoption occurs), we can represent the technological space as a network. This representation proves to be useful as it allows identification of the spread of each co-adoption and of the occurrence of multiple co-adoptions, and observation of the whole network of co-adoptions over time. Figure 1 below illustrates the evolution of the regional technological space between 2008 and 2018. In 2008 the technological space was still quite under-developed. Two technologies had not yet been adopted by the sample firms: Block Chain and Virtual Reality. By 2018 the space had evolved substantially. The technological space is now centred on the quadrilateral of ties that connect Automations & Robotics with Cybersecurity, and also Cloud Services and I.o.T. From 2008 to 2018 two interconnected factors changed. Firstly, the spread of adoption of each technology, which increased substantially over time from an average of 19.77 firms per technology, to an average of 148.44 (see Table 2). Secondly, the spread of co-adoptions, captured by the high number of ties of each technology (measured by its degree centrality). As Table 2 clearly shows, while the whole network was quite disconnected in 2008 (average degree centrality was 3.55) almost all technologies were co-adopted by 2018 (average degree centrality was 7.77). A case in point is Cloud Services, adopted by 8 firms in 2008 with a degree centrality equal to 5, and finally adopted by 209 firms with 8 as degree centrality in 2018. At the other end of the spectrum we find Artificial Intelligence. Despite the fact that this technology is usually considered among the most impactful in terms of gains in decision making, process automation and adaptation, its use remains limited (there were only 28 adopters in 2018), with a potential that is clearly not fully exploited yet by the regional system. One possible explanation for this is that it may be still relatively isolated as a technology, being only seldom connected to other more widespread technologies: in Table 2 we can easily see that only a few firms are involved in the ties springing from the Artificial Intelligence node. Other technologies that are deemed to be very impactful seem to have a similar fate to Artificial Intelligence. This is the case of Virtual Reality, potentially supporting firms in any innovation by providing a sandbox for experimentation, and yet largely underemployed in the region. Also in this case, the connection to other commonly used technologies is likely key: when related to technologies such as Automation & Robotics or I.o.T, Virtual Reality can contribute significantly to the generation of new value added. If such a connection does not occur, Virtual Reality risks remaining a simple add on.

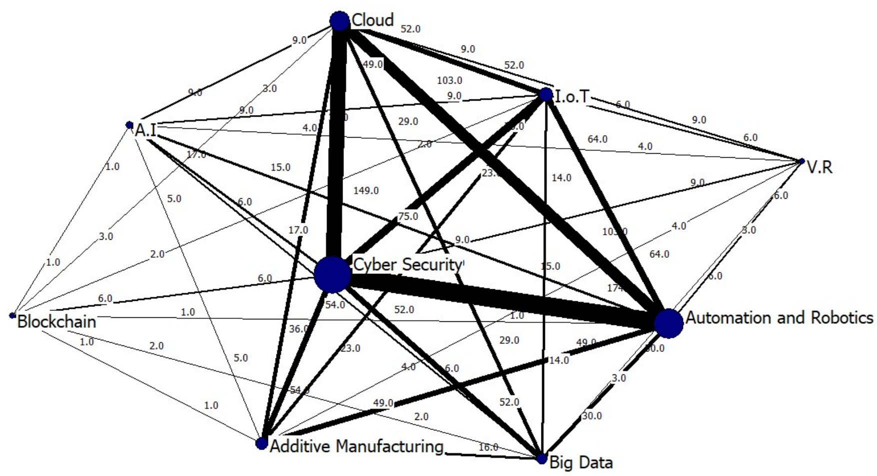
As this preliminary investigation into the technological space of the region shows, while digital technologies spread and have been co-adopted more frequently over time, there is a clear 'technological backbone' to the space, that started with the contemporaneous adoption of Automations & Robotics and Cybersecurity, and moved on to the quadrilateral connecting these elements with Cloud Services and I.o.T.. Other technologies that are only loosely linked to the emerging quadrilateral are also co-adopted to a certain degree, but remain peripheral within the technological space of the region.

Figure 1 – The evolution of the technological space of the Veneto region

Year 2008



Year 2018



Source: Our own elaboration of the Unioncamere dataset using UNICET software (Borgatti Everett & Freeman 2002). Node size corresponds to the number of adopters of that technology in the sample firms. A tie between technologies A and B is formed when a firm adopts both technologies. In particular the weight of a tie (reported on the graph as a number on the ties) represents the number of firms adopting the linked technologies.

Table 2 –Presence and role of technologies in 2008 and 2018

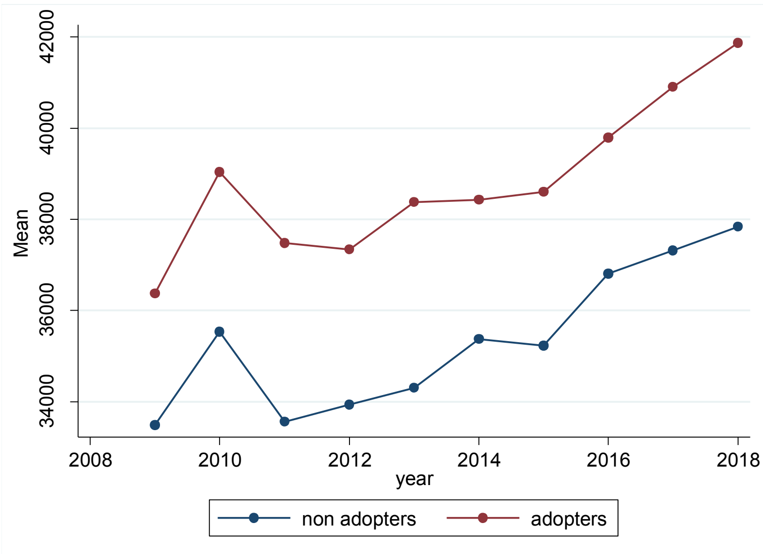
	2008		2018	
Type of technology	**N.of adopters**	**Degree centrality***	**N.of adopters**	**Degree centrality**
Artificial Intelligence (A.I)	6	4	28	8
Automation and Robotics	68	6	346	8
Additive manufacturing	5	3	104	8
Internet of Things (I.o.T)	18	4	111	8
Virtual reality (V.R)	0	0	13	7
Cloud Services	8	5	209	8
Cyber Security	66	6	446	8
Big Data	7	4	72	8
Blockchain	0	0	7	7
Average	19.77	3.55	148.44	7.77

*The degree centrality indicates the number of ties connecting one technology to the others.
Source: Our own elaboration of the Unioncamere dataset.

WORKFORCE DYNAMICS AND TECHNOLOGICAL SPACE

As the technological space evolves, we expect to see an increase in the employment of a highly-qualified workforce. The chart below (Figure 2) reports the evolution from 2008 to 2018 of the annual average labour cost, distinguishing adopter firms (that adopted at least one technology) and non-adopters (that never did so).

Figure 2 – Trends of average labour cost (expressed in euros) of technological adopters and non-adopters (years: 2008-2018)



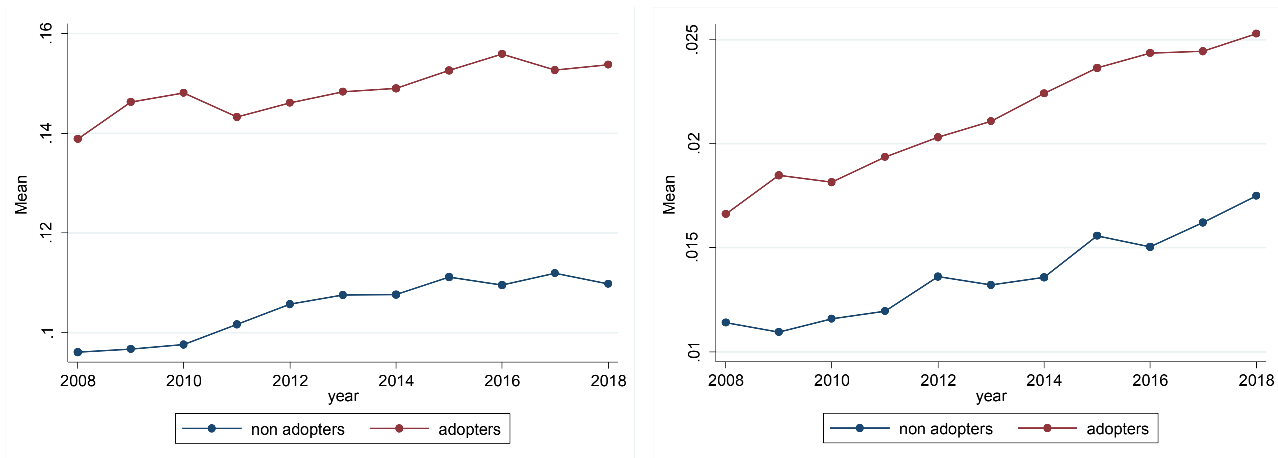
Source: Our own elaboration of the integrated dataset

When data relating to a small number of structural contingencies is removed, the annual average labour cost can be considered a proxy to measure changes in the quality of the workforce. Through this lens, we can observe a positive trend for the sample firms, particularly from 2012 onward, while the average labour cost always remains higher for adopter firms. This means that, although adopters moved from a higher level of both ratios, we do not detect major differences between the path followed by technology adopters and non-adopters, even if the former do introduce new technologies over the observation period and the latter do not. Quite surprisingly, all firms invested in strengthening the qualifications of their workforce despite technology adoption.

We dig deeper into this intuition by reporting the evolution over time of two average ratios: the first between the number of technicians and the overall number of employees (chart a) and the second between the number of scientific specialists and the same denominator (chart b), again distinguishing between adopters and non-adopters[4]. Figure 3 reports the charts.

Figure 3 - Trends of technicians and scientific specialists ratios for technological adopters and non-adopters (years: 2008-2018)

a) technician ratio *b) scientific specialist ratio*



Source: Our own elaboration of the integrated dataset

Despite the fact that adopters always employed a larger proportion of specialized workers than non-adopters, the similarities among the paths followed by the two groups are striking, as both groups increase their ratio of technicians and -more quickly- that of scientific specialists in similar proportions. Moreover, we observe no significant difference between adopters and non-adopters in the marginal increase in the proportion of technicians and scientific specialists, even if the former adopt new technologies and non-adopters never do so. In other words, there is no clear evidence of any adopters' accelerating their acquisition of a more specialized workforce.

From the previous insights, it might be intuited that no relation exists between virtuous strategies in terms of occupational dynamics, and virtuous behaviours in terms of technology adoption. However, it may be difficult to reach such a conclusion pooling all technological adoptions into one dichotomous

[4] From 2008 a National Law obliges firms to communicate of each and every hired employee. Thus, data about long-term employees hired before 2008 may not be available. Thus, the variables in the charts, rather than representing the actual stock of employees for each year, should be considered in terms of their change over time.

indicator adopters/non-adopters, without any exploration of the timing of the adoption nor of the specific technologies adopted. We try to dig deeper into this point using a regression analysis. The models are intended to investigate the contemporaneous and future occupational effect, in terms of firms' employment ratio of technicians and scientific specialists, of the adoption events of specific digital technologies.

The models

The econometric models we used to investigate the relationship between firms' occupational choices and firms' technology adoption need to take into account the particular distribution of the dependent variables employed. The dependent variables are ratios (technicians over total workforce, and scientific specialists over workforce) with lower bound 0 and upper bound 1. OLS is not suitable as observations lying on the boundaries may lead to negative predicted values. In such case, Generalized Linear Models (GLM) specified with a binomial family and a logit link function (due to the observations standing between 0 and 1) are valid alternatives (Papke & Wooldridge, 1996). We thus move from the following specification:

$$G\big(E(Y)\big) = \alpha + \sum\nolimits_{K=1}^{K} \beta_k X_{ik}$$

Where *G(E(Y))* is the function of the expected value of *Y*, the dependent variable, including the specification of family (binomial) and link (logit). The models in Table 3 employ the technician ratio as dependent variable, while those in Table 4 use the scientific-specialist ratio. We investigated how these dependent variables are affected by a series of independent variables. In Model A, the main independent variable is a dummy marked as 1 for the year in which the firm has adopted at least one technology. In Model B, it is substituted by the number of technologies adopted in each specific year.

In model Model C it is replaced by a series of dummies, one for each technology, marking as 1 the year of adoption. To capture the possible lag structure in the relation between previous (or contemporaneous) technology adoption and future (or contemporaneous) firms' occupational choices, we also produced other regressions where we lagged the regressors by one or two years. In all models we controlled for firm size in terms of employees and for the type of production performed by the firms (capital, intermediate or customer goods). For all regressions, we included year dummies and computed robust standard errors to avoid heteroskedasticity. Appendix A reports the main statistics for the variables, while Appendix B reports correlations between the variables used in the different regressions. It is easy to see from Appendix B that multicollinearity should not be a problem as all correlations are below 0.20, with only one being 0.67, in any case well below the conventional level of 0.80.

Table 3 - Generalized linear model - Dependent variable: technician ratio

Dependent var.	**Model A**			**Model B**			**Model C**		
	Lag_2	Lag_1	Lag_0	Lag_2	Lag_1	Lag_0	Lag_2	Lag_1	Lag_0
Adoption of technologies	**0.319*** **	**0.331*** **	**0.235*** **						
	(0.052)	(0.047)	(0.040)						
Num. of technologies introduced in that year				**0.192*** **	**0.200*** **	**0.142*** **			
				(0.038)	(0.032)	(0.027)			
Artificial Intelligence							**-0.778** **	-0.313	**-0.648** **
							(0.369)	(0.321)	(0.257)
Automation & Robotics							**0.205* **	**0.145* **	0.046
							(0.107)	(0.088)	(0.071)
Additive manufacturing							**0.600*** **	**0.676*** **	**0.648*** **
							(0.160)	(0.137)	(0.121)
Internet of Things							-0.024	0.009	-0.057
							(0.178)	(0.134)	(0.110)
Virtual & Augmented Reality							0.245	-0.121	0.305
							(0.269)	(0.298)	(0.278)
Cloud Services							**0.276** **	**0.328*** **	**0.262*** **
							(0.120)	(0.101)	(0.080)
Cyber Security							**0.157* **	0.088	0.085
							(0.081)	(0.071)	(0.059)
Big Data							0.168	**0.248* **	**0.247* **
							(0.144)	(0.138)	(0.128)
Blockchain							-0.252	-0.083	-0.471
							(1.092)	(1.105)	(0.362)
Medium firm	0.368***	0.365***	0.366***	0.369***	0.367***	0.367***	0.368***	0.365***	0.365***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Large firm	0.392***	0.390***	0.387***	0.393***	0.392***	0.387***	0.391***	0.389***	0.384***
	(0.040)	(0.041)	(0.041)	(0.040)	(0.041)	(0.041)	(0.040)	(0.041)	(0.041)
Intermediate goods	-0.633***	-0.631***	-0.631***	-0.632***	-0.631***	-0.631***	-0.633***	-0.630***	-0.629***
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
Customer goods	-0.657***	-0.655***	-0.654***	-0.657***	-0.655***	-0.654***	-0.657***	-0.654***	-0.654***
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
Year dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes
_cons	-1.636***	-1.636***	-1.638***	-1.636***	-1.636***	-1.637***	-1.635***	-1.636***	-1.636***
	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)
Obs.	17575	17575	17575	17575	17575	17575	17575	17575	17575

Standard errors are in parenthesis. Excluded dummies: small firm; capital goods

****** p<0.01, ** p<0.05, * p<0.1. Mean dependent var. 0.125; SD dependent var: 0.147*

Table 4 - Regression results – Dependent variable: scientific-specialists ratio

Dependent var.	**Model A**			**Model B**			**Model C**		
	Lag_2	Lag_1	Lag_0	Lag_2	Lag_1	Lag_0	Lag_2	Lag_1	Lag_0
Adoption of technologies	**0.238****	**0.183****	**0.141***						
	(0.099)	(0.087)	(0.082)						
Num. of technologies introduced in that year				**0.145****	**0.109****	0.079			
				(0.057)	(0.053)	(0.054)			
Artificial Intelligence							**-1.098*****	**-0.965*****	**-0.872*****
							(0.357)	(0.309)	(0.318)
Automation & Robotics							-0.023	**-0.281***	**-0.316****
							(0.155)	(0.144)	(0.129)
Additive manufacturing							0.293	**0.329***	**0.531****
							(0.269)	(0.177)	(0.257)
Internet of Things							0.202	0.073	0.111
							(0.302)	(0.258)	(0.233)
Virtual & Augmented Reality							-0.095	0.129	**0.385***
							(0.233)	(0.248)	(0.210)
Cloud Services							0.235	0.279	**0.318***
							(0.284)	(0.207)	(0.168)
Cyber Security							0.197	**0.217***	0.036
							(0.148)	(0.132)	(0.111)
Big Data							0.314	0.187	0.070
							(0.261)	(0.256)	(0.240)
Blockchain							**-10.312*****	**-10.337*****	-0.460
							(0.874)	(0.864)	(0.392)
Medium firm	0.685***	0.686***	0.686***	0.686***	0.687***	0.687***	0.685***	0.686***	0.684***
	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)
Large firm	1.078***	1.079***	1.077***	1.079***	1.080***	1.077***	1.077***	1.078***	1.075***
	(0.091)	(0.091)	(0.091)	(0.090)	(0.090)	(0.091)	(0.091)	(0.091)	(0.092)
Intermediate goods	-0.390***	-0.389***	-0.389***	-0.390***	-0.389***	-0.389***	-0.389***	-0.385***	-0.385***
	(0.062)	(0.062)	(0.062)	(0.062)	(0.062)	(0.062)	(0.062)	(0.062)	(0.061)
Customer goods	-0.003	-0.001	-0.001	-0.003	-0.002	-0.001	-0.003	0.000	-0.001
	(0.058)	(0.058)	(0.058)	(0.058)	(0.058)	(0.058)	(0.058)	(0.058)	(0.058)
Year dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes
_cons	-4.329***	-4.329***	-4.330***	-4.329***	-4.329***	-4.330***	-4.329***	-4.330***	-4.329***
	(0.110)	(0.110)	(0.110)	(0.110)	(0.110)	(0.110)	(0.110)	(0.110)	(0.110)
Obs.	17575	17575	17575	17575	17575	17575	17575	17575	17575

Standard errors are in parenthesis. Excluded dummies: small firm; capital goods

**** p<0.01, ** p<0.05, * p<0.1. Mean dependent var. 0.017; SD dependent var: 0.052*

RESULTS

Table 3 and Table 4 subvert our previous intuition: both the technician and scientific specialist ratio significantly and positively relate to the specific event of technology adoption by the firm, and to the number of technologies adopted by the firms in that or previous years. In fact, the effect on the ratio seems generally stronger one year after technological adoption, and even stronger after two years, with coefficients increasing from 35% up to 80%.

In Table 3 the technician ratio appears negatively associated to the adoption of Artificial Intelligence, even if in this case the small number of adopting firms should flash a warning. However, in support of the latter result comes the analysis relative to the scientific-specialist ratio reported in Table 4: here too the adoption of Artificial Intelligence has a negative effect on the specialists' proportion, for all lags.

Another result that is common to the two groups of specialists, and strong in statistical terms, is the positive association between the occupational ratio and the adoption of Additive Manufacturing. The effect is particularly relevant for technicians, where the coefficient of the technology adoption dummy for scientific specialists is larger and more significant across the whole lag structure. Cloud Services have a very significant and positive effect on technician ratio, for all lags, and still a positive and sizable effect for the scientific specialist ratio, even if this effect disappears after one year. Cyber Security also has a positive and significant effect for both specialist categories, even if only for lag. Big Data shows a positive effect that lasts between one and two years, but only for technicians. The ratio for scientific specialists, on the contrary, seems not to be sensitive to the adoption of Big Data technologies. The analysis highlights a peculiar effect of Automation & Robotics: it relates significantly to both ratios of specialist presence in the firms' workforce, but in opposite ways. It has a significant and positive relation to technician ratio, and a negative effect on the scientific-specialist ratio. Finally, Blockchain (which concerns mainly payment systems) has a strong and negative effect only for the scientific-specialist ratio, as does Virtual & Augmented Reality, even if in this latter case the effect is positive. Due to the low number of observations capturing adoption of these two technologies, we must be very cautious in assessing these last results.

In terms of the effect of controls, the increase of the two profile ratios concerns more firms reaching a certain size (medium or large), as well as firms specialized in the production of capital goods, which are also more involved in sectors that concern the production of machines and apparatus to be employed in the productive processes of other firms.

Robustness check

The first check regards the intragroup correlation possibly affecting observations from the same firms. To control for this, we re-run our regressions clustering the standard errors according to the firm identifier. Our results map almost perfectly those reported in Tables 3 and 4.

As a second check, we observed that the Unioncamere dataset reports firms' class size for year 2018 only. Even if we cannot choose to study the variation of the variable over time, we chose to use this variable as it appears to be the most reliable. We have done this also as a result of the (plausible) assumption that the number of firms whose size varies so much that they switch from one class (small, medium and large) to another during our 10-year period (2008-2018) is small enough not to create serious biases in our estimates. To be perfectly sure, however, we run our regressions without those variables, using instead information about firms' size available in the AIDA dataset; information that is not as reliable, but retrievable for all years. The regressions were run for a total of 11745 available observations. The check confirms the robustness of our main results, both in relation to the moment of the adoption of the technology and in relation to the number of technologies adopted in each year.

As a further check, we performed our main regressions substituting the wider categories of 'Type of production' with the more granular definition of 'Manufacturing sectors' (as per Table 1). Our main results are confirmed, by and large, raising some doubts only for the role played by Augmented Manufacturing and Cloud services for scientific-specialists, where they lose significance[5].

As regards the adoption of specific technologies, some differences emerge. The timing of the adoption of Blockchain acquires a significantly negative relation to technician ratio, while Virtual & Augmented Reality loses its significance. The results for these two technologies are thus either quite erratic or very weak, and this, coupled with the low number of firms adopting them, speaks in favour of leaving these

[5] In line with the positive significance that emerges for those firms producing capital goods compared to firms in which the specialization is mainly in the intermediary or customers goods, we notice that the ratio is significantly positive for firms in sectors such as mechanical machines and apparatus and electrical and electronic machines compared to sectors such as textiles more traditionally anchored to the 'Made in Italy' market products.

findings aside, calling for future research in this area. The robustness checks for other technologies, such as Cybersecurity, Big Data Analytics, also show no particular significance, thus requiring the relative results to be interpreted with much care. The robustness checks give more consistent results for A.I, Automation & Robotics, Cloud Services and Additive Manufacturing, which thus represent the most solid results we have produced.

DISCUSSION AND CONCLUSION

The paper aimed to investigate the relationship between the evolution of a regional technological space and the changes in local firms' workforce composition, looking at the dynamics of two specific workers profiles that correspond to two different typologies of knowledge base: technicians (linked to synthetic knowledge) and scientific specialists (linked to analytical knowledge).

We first investigated the network of co-adoptions in the period 2008 – 2018 of all the 9 considered technologies (Artificial Intelligence, Automations & Robotics, Additive Manufacturing, Internet of Things, Virtual and Augmented Reality, Cloud Services, Cyber Security, Big Data Analytics and Blockchain) by the firms in our sample (i.e., 1800 firms located in the Veneto Region in Italy). We observe a clear pattern of technology diffusion, leading to a denser network of co-adoptions, that however leaves some of the most promising technologies, such as Artificial Intelligence, aside. A 'backbone' of the regional technological space gradually emerges around four main co-adopted technologies: Automations & Robotics and Cybersecurity (co-adopted the most, since 2008), and Cloud Services and I.o.T (entering the backbone of mostly co-adopted technologies later in the process).

Firm-wise, this evolution corresponds to the adoption by many companies of 'less sophisticated' technologies, such Automation & Robotics, or 'auxiliary technology' such as Cyber Security, while many firms simply did not invest in any 4.0 technological asset within the time window of our analysis.

The adoption of the enabling technologies of Industry 4.0 by only part of the local firms may result in unequal opportunities in the region, with important negative consequences on regional renewal. In a long-term perspective, this may increase the risk of skill polarization, and might create a loss of competitiveness for smaller firms or firms serving the traditional 'Made in Italy' final markets.

In this respect, the paper also demonstrates that in a manufacturing region like the Veneto the adoption of Industry 4.0 enabling technologies may trigger some adaptive processes that have important effects on local occupational dynamics. Our descriptive analysis shows that workforce composition among firms adopting enabling technologies leans toward a higher presence of technicians and scientific specialists. However, this is true for the initial stock of workers. Even if adopters employ a constantly growing number of technicians and scientific specialists, both adopters and non-adopters strengthen over time the specialized component of their workforce following very similar pathways, so that the co-evolution of occupational choices and digital technology adoption seems very weak. Overall, the dynamics of digital technology adoption thus seem to be *unrelated* to changes in firms' occupational choices over time. How close to reality is this counterintuitive intuition?

We further investigated this point by a regression analysis which looks at such a relationship year by year, and which also compares different years, and through a more granular lens disentangling the effect of each digital technology. First of all, we observe an increase in the proportion of technicians and scientific specialists when firms adopt or increase their technological portfolio. This effect is contemporaneous, and increasing as time goes by. This suggests that firms need to gradually adapt their workforce to the adopted technologies, possibly to compensate for an initial underestimation of their competence needs.

Moreover, the positive relation between on the one hand firms' technological adoption/number of technologies adopted in each year, and on the other hand scientific specialist ratio is weaker and less significant compared to the technician ratio. Thus, the relationship between adoption and employment is tighter for profiles that help the firm to acquire synthetic rather than analytical knowledge.

In terms of specific technologies, the result regarding Artificial Intelligence lends support to the idea that this technology is substituted, on the one hand, by the operative tasks of technicians, and, on the other hand, by the analytical decision-making processes performed by scientific specialists. Additive Manufacturing and Cloud services, and with less solidity also Cyber Security and Big Data, have the opposite function of Artificial Intelligence: A.I. may *substitute* specialists' tasks, while these technologies may *complement* specialists' competencies, especially those based on synthetic knowledge (technicians). Big Data in particular clearly has a supportive role to decision making, enhancing, rather than contrasting, the employment of specialists by the firm. However, that seems to be true mainly for technicians. Surprisingly, adopting Big Data as a technology does not relate in any way to the presence of scientific-specialists, meaning that its complementary role addresses mainly synthetic knowledge. Additive Manufacturing also has a different positive role in the two specialist categories: it adds flexibility to production and thus allows more experimentation and innovation, but its application is linked to processes of product development, and may thus require the employment of more synthetic knowledge rather than analytical knowledge. Automation & Robotics take this differentiation to a higher level, having a significant and positive relation to technician ratio and a negative and significant relation with the scientific-specialist ratio. Implementing automation and including robots in the productive process is complementary to know-how and thus requires synthetic knowledge, but it possibly diverts attention from efforts to ease complex decision making towards the acquisition of flexibility and speed on the production floor, resulting in underinvestment in the acquisition of a more analytical knowledge base and the mastering of it by workers

A final result is worth mentioning: while I.o.T. becomes increasingly central over time in the technological space, with its adoption spreading and it being co-adopted with the other main technologies, it does not seem to be related to the dynamics of firms' investment in specialized employees. This is probably due to the nature of this technology, which can be conceived as an infrastructure applied to processes for which what matters is an initial investment at the moment of installation, possibly by external suppliers, without much need for the development of related internal competences.

Putting all these results together, the picture that emerges is multifaceted. Adoption of digital technologies in a traditional but heavily industrialized region like the Veneto does relate to the occupational choices of local firms over time, contemporaneously and even more after some years. But this is less visible in aggregate terms, as other factors may explain local firms' occupational choices and the effects of different technologies on different types of specialists are not all in the same direction, blurring the picture with quite mixed dynamics. Discovering -as we do here- that AI is a substitute for all specialists, that Automation & Robotics is a substitute only for scientific specialists while enhancing the work of technicians, and that Additive Manufacturing and Cloud services are complementary to both categories, is significant and gives depth to the occupation-technology nexus dynamics. Similarly, the finding that I.o.T in fact does *not* relate to firms' occupation choices, despite its importance in the emerging 'quadrilateral' of the key technologies that constitute the backbone of the regional technological space, shows that not all digital technologies have a strong relation to specialists' knowledge bases and to hiring processes. Finally, our analysis of the evolution of the technological space itself highlights connectivity among digital technologies - i.e., the spread of co-adoption - but it also captures the disparities amongst firms that are quite advanced along the Industry 4.0 development path, and others that lag behind.

The results clearly have implications in terms of policy and can provide information to policymakers regarding the weakness and strengths of the co-evolution of technological digital spaces and occupational dynamics in a traditional and heavily industrialized region like the Veneto.

First, investments for the development of regional technological competitiveness cannot be focused only on providing access to digital infrastructure. They need to support firms' development of a strategic approach toward technological adoption. In particular, when the region faces the disruptive challenges brought about by Industry 4.0, policy makers should aim to reduce the skill gap, especially for those companies that still exhibit lower rates of employment of specialized profiles. Policy should support the employment of specialists with scientific profiles, but also – and especially – those with technical profiles, who are able to bring into firms a synthetic knowledge base that, even more than an analytical knowledge base, eases the adoption of digital technology.

Further policy implications can also be retrieved from the analysis of the different technologies. Some digital technologies (e.g., I.o.T.) do not seem to require specific specialists in order to be adopted, while other have a positive (e.g., Augmented Manufacturing) or negative (A.I.) relation to specialized profiles of all categories, while others (Automation & Robotics) favour firms' acquisition of synthetic knowledge (via the hiring of technicians) and discourage the acquisition of analytical knowledge (decreasing the proportion of scientific specialists). These effects suggest that digital technologies cannot all be treated as equal: their relationship with firms' occupational choices is quite idiosyncratic. This must be taken into account when designing policies aimed at fostering the adoption of digital technologies, distinguishing one from the other.

Further research should be devoted to deepening the analyses of the occupational dynamics of technicians and scientific specialists. More granular data at the level of employees may provide broader insight regarding the specific functions performed by those profiles. Future research should also be aimed at investigating how firms' adoption of digital technologies affects other workers' profiles, such as blue-collar workers, who are in charge of more routinized tasks and semi-automatic processes.

BIBLIOGRAPHY

Asheim, B.T., & Coenen, L. (2005). Knowledge bases and regional innovation systems. Comparing Nordic clusters. *Research Policy*, 34(8), 1173–1190.

Becattini, G. (2001). *The Caterpillar and the Butterfly: An Exemplary Case of Development in the Italy of the Industrial Districts*, Firenze: Felice Le Monnier.

Bellandi, M., Chaminade, C., & Plechero, M., 2020. Transformative paths, multi-scalarity of knowledge bases and Industry 4.0. In De Propris, L. & D. Bailey (eds.). *Industry 4.0 and Regional Transformations*. London: Routledge.

Borgatti, S.P., Everett, M.G. and Freeman, L.C. (2002). *Ucinet 6 for Windows: Software for Social Network Analysis*. Harvard, MA: Analytic Technologies.

Boschma, R., Iammarino, S. & Steinmueller, E. (2013), Geography, Skills and Technological Change, *Regional Studies*, 47 (10), 1615-1617.

Brynjolfsson, E., & McAfee, A. (2014). The Second Machine Age. Work, Progress and Prosperity in a Time of Brilliant Technologies. W.W. Norton & Company, US.

Büchi, G., Cugno, M., & Castagnoli, R. (2020), Smart factory performance and Industry 4.0. *Technological Forecasting and Social Change*, 150 https://doi.org/10.1016/j.techfore.2019.119790.

Castellacci, F., Consoli, D & Santoalha, A. (2019). The role of e-skills in technological diversification in European regions, *Regional Studies*, Online first. Doi: 10.1080/00343404.2019.1681585.

Chaminade, C., Bellandi, M. Plechero, M. & Santini E., (2019). Understanding processes of path renewal and creation in thick specialized regional innovation systems. Evidence from two textile districts in Italy and Sweden. *European Planning Studies*, 27 (10), 1978-1994.

Coenen L., Moodysson. J., Ryan, C., Asheim, B. & Phillips, P., (2006). Comparing a pharmaceutical and an agro-food bioregion: on the importance of knowledge bases for socio-spatial patterns of innovation. *Industry and Innovation*, 13, 393-414.

Corò, G. & Volpe, M. (2020). Driving factors in the adoption of Industry 4.0 technologies. An investigation of SMEs. In De Propris, L. & D. Bailey (eds.). *Industry 4.0 and Regional Transformations*. London: Routledge.

De Propris, L. & Bailey, D. (eds.) (2020), Industry 4.0: Transformational Regions, Routledge.

Filippetti, A. Frederick G. & Iammarino, S. (2019) Regional disparities in the effect of training on employment, Regional Studies, 53:2, 217-230, DOI: 10.1080/00343404.2018.1455177.

Fritsch, M., Kudic, M. & Pyka, A. (2019) Evolution and co-evolution of regional innovation processes, Regional Studies, 53:9, 1235-1239, DOI: 10.1080/00343404.2019.1627306.

Frenken, K., Van Oort, F., & Verburg, T. (2007) Related variety, unrelated variety and regional economic growth, *Regional Studies*, 41: 685-697.

Geissbauer, R., Schrauf, S., Koch, V., (2014). Industry 4.0: Opportunities and Challenges of Industrial Internet, PricewaterhouseCoopers. Freudenberg IT. Available at: https://www.pwc.nl/en/assets/documentAhlers, T, 2015. Industrie 4.0: The Big Unknown?

Grabher G. (1993), The Weakness of Strong Ties: The Lock-in of Regional Development in the Ruhr Area. In G. Grabher (Ed.), *The Embedded Firm: On the Socioeconomics of Industrial Networks*, (pp. 255-277). Routledge: London.

Grillitsch, M, Schubert, T., Srholec, M., (2019). Knowledge base combinations and firm growth. *Research Policy*, 48 (1), 234-247.

Grillitsch, M, Martin, R. and Srholec, M. (2017). Knowledge Base Combinations and Innovation Performance in Swedish Regions. *Economic Geography*, 93:5, 458-479.

Grillitsch, M., Asheim, B.T and Trippl, M. (2018). Unrelated knowledge combinations: the unexplored potential for regional industrial path development, *Cambridge Journal of Regions, Economy and Society*. Advanced online publication doi.org/10.1093/cjres/rsy012.

Isaksen, A., & Trippl, M. (2016). Path development in different regional innovation systems. A conceptual analysis. In D. Parrilli, R. D. Fitjar, & A. Rodriguez-Pose (Eds.), *Innovation drivers and regional innovation strategies* (pp. 66–84). New York and London: Routledge.

Jensen, M.B., Johnson, B., Lorenz, E. & Lundvall, B. (2007). Forms of knowledge and modes of innovation. Research Policy 36:680–693.

Kiel, D., Arnold, C., & Voigt, K.I. (2017). The influence of the Industrial Internet of Things on business models of established manufacturing companies–A business level perspective. *Technovation* 68, 4–19.

Krzywdzinski, M. (2017). Automation, skill requirements and labour□use strategies: high□wage and low□wage approaches to high□tech manufacturing in the automotive industry, new technology. *Work Employ*. 32 (3), 247–267.

Martin, R. & Sunley, P. (2006) Path dependence and regional economic evolution, *Journal of Economic Geography*, 6: 395-437.

Ministero dello Sviluppo Economico (2018a). Piano nazionale industria 4:0. https://www.mise.gov.it/images/stories/documenti/guida_industria_40.pdf .

Ministero dello Sviluppo Economico (2018b) La diffusione delle imprese 4.0 e le politiche: evidenze 2017. www.sviluppoeconomico.gov.it/images/stories/documenti/Rapporto-MiSE-MetI40.pdf

MacKinnon, D., Cumbers, A., & Chapman, K. (2002). Learning, innovation and regional development: a critical appraisal of recent debates. *Progress in Human Geography*, *26*(3), 293–311.

Neffke, F., Henning, M., & Boschma, R. (2011). How do regions diversify over time? Industry relatedness and the development of new growth paths in regions. *Economic Geography*, 87(3), 237-265.

Nelson, R.R., (2004). The market economy and the scientific commons. Research Policy 33, 455–471.

Papke, L & Wooldridge, J. (1996). Econometric Methods for Fractional Response Variables with an Application to 401(K) Plan Participation Rates *Journal of Applied Econometrics*, 11, 6, 619–32.

Peck, J. A., & Haughton, G. F. (1991). Youth training and the local reconstruction of skill: Evidence from the engineering industry of Regional disparities in North West England, 1981–88. Environment and Planning A, 23, 813–832.

Raj, A., Dwivedi, G. Sharma, A, Jabbour, A. , Rajak, S. (2019) Barriers to the adoption of industry 4.0 technologies in the manufacturing sector: An inter-country comparative perspective, *International Journal of Production Economics*. Online first. https://doi.org/10.1016/j.ijpe.2019.107546.

Teece D.J. (1996). Firm organization, industrial structure, and technological innovation, Journal of Economic Behavior & Organization, 31(2), 193–224.

Appendix A – Descriptive statistics, sources and description of the data used in the regression model

Source	Variable	Description	Obs	Mean	Std. Dev.	Min	Max
Veneto Lavoro	Technician ratio	Ratio (lower bound 0; upper bound 1) of total technicians over the stock of employees	17575	.1251914	.1469127	0	1
	Scientific-specialist ratio	Ratio (lower bound 0; upper bound 1) of total scientific specialists over the stock of employees	17575	.017202	.0523854	0	1
Unioncamere Veneto	Adoption of technologies	Dummy variable: 1 the year in which the firm has adopted at least one technology, 0 otherwise	17575	.051835	.2217001	0	1
	Num. of technologies introduced in that year	Number of technologies adopted by the firm in that specific year	17575	.0649218	.3085339	0	7
	Artificial Intelligence	Dummy variable: 1 the year in which the firm has adopted Artificial Intelligence, 0 otherwise	17575	.0012518	.0353593	0	1
	Automation & Robotics	Dummy variable: 1 the year in which the firm has adopted Automation & Robotics, 0 otherwise	17575	.0158179	.1247742	0	1
	Additive manufacturing	Dummy variable: 1 the year in which the firm has adopted Additive Manufacturing, 0 otherwise	17575	.0055192	.0740882	0	1
	Internet of Things	Dummy variable: 1 the year in which the firm has adopted Internet of Things, 0 otherwise	17575	.0051778	.0717725	0	1
	Virtual & Aug. Reality	Dummy variable: 1 the year in which the firm has adopted Dummy variable: 1 the year in which the firm has adopted V.R., 0 otherwise	17575	.0006259	.0250107	0	1
	Cloud Services	Dummy variable: 1 the year in which the firm has adopted Cloud Services, 0 otherwise	17575	.0110384	.1044853	0	1
	Cyber Security	Dummy variable: 1 the year in which the firm has adopted Cyber Security, 0 otherwise	17575	.0214509	.1448861	0	1
	Big Data	Dummy variable: 1 the year in which the firm has adopted Big Data, 0 otherwise	17575	.0036415	.0602369	0	1
	Blockchain	Dummy variable: 1 the year in which the firm has adopted Blockchain, 0 otherwise	17575	.0003983	.0199539	0	1
	Small firm	Dummy variable: 1 if the firm has ≤49 full time equivalent employees (FTE), 0 otherwise	17575	.7929445	.4052072	0	1
	Medium firm	Dummy variable: 1 if the firm has between 50 and 249 FTE, 0 otherwise	17575	.1782646	.3827462	0	1
	Large firm	Dummy variable: 1 if the firm has ≥250 FTE, 0 otherwise	17575	.0287909	.1672231	0	1
	Capital goods	Dummy variable: 1 if the firm is producing mainly capital goods, 0 otherwise	17575	.195505	.3966002	0	1
	Intermediate goods	Dummy variable: 1 if the firm is producing mainly intermediate goods, 0 otherwise	17575	.4793741	.4995886	0	1
	Customer goods	Dummy variable: 1 if the firm is producing mainly customer goods, 0 otherwise	17575	.3251209	.4684333	0	1
	Adopters*	Dummy variable: 1 if the firms has adopted a technology, 0 otherwise	17575	.4583784	.4982788	0	1
AIDA	Labour cost*	Continuous variable indicating the annual average cost of labour per employee	11316	37236.02	11930.28	1180	98140

*Variable used for Figure 2, 3 and 4

Appendix B – Correlations among the main variables included in the regressions (missing correlations correspond to variables that never co-occur in the same regression)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1) Technician ratio																	
(2) Scientif-specialist ratio																	
(3) Adoption of technologies	0.06*	0.03*															
(4) Num. of technologies introduced in that year	0.06*	0.03*															
(5) Artificial Intelligence	-0.01	-0.00															
(6) Automation & Robotics	0.02*	-0.00			0.09*												
(7) Additive manufacturing	0.06*	0.03*			0.06*	0.04*											
(8) Internet of Things	0.01	0.01			0.11*	0.13*	0.07*										
(9) Virtual & Aug. Reality	0.02*	0.01			0.19*	0.03*	0.03*	0.09*									
(10) Cloud Services	0.04*	0.03*			0.03*	0.13*	0.09*	0.17*	0.04*								
(11) Cyber Security	0.03*	0.01			0.03*	0.09*	0.03*	0.10*	0.03*	0.19*							
(12) Big Data	0.03*	0.01			-0.00	0.05*	0.03*	0.02*	0.04*	0.05*	0.11*						
(13) Blockchain	-0.00	0.00			-0.00	-0.00	0.04*	0.04*	-0.00	0.05*	0.04*	0.05*					
(14) Medium firm	0.12*	0.10*	0.06*	0.07*	0.01	0.03*	0.03*	0.01	0.01	0.06*	0.04*	0.02*	0.01				
(15) Large firm	0.05*	0.08*	0.03*	0.04*	0.00	0.03*	0.03*	0.03*	0.04*	0.01	0.00	0.02*	0.01	-0.08*			
(16) Intermediate goods	-0.11*	-0.07*	-0.00	-0.01	-0.01	0.02*	-0.02*	0.00	-0.01*	-0.00	-0.02*	-0.01	-0.01	-0.08*	-0.05*		
(17) Customer goods	-0.08*	0.04*	-0.02*	-0.02*	0.00	-0.02*	-0.00	-0.02*	-0.00	0.00	-0.00	-0.01	0.00	0.03*	0.02*	-0.67*	

** *p<0.05*