Firm Competitiveness, Specialisation, and Employment Growth: Territorial Level Relationships

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Abstract The concept of competitiveness is today a central element for regional development, European cohesion policies and smart specialisation strategies. Despite being born for firm-level analyses, competitiveness is indeed commonly used at the territorial level, mainly at the regional or urban scale, normally measured with different composite structural indicators. However, since territorial competitiveness is unevenly distributed in space, territorial units smaller than a full NUTS-2 region might be differently competitive and hence suited to implement differentiated cohesion policies and smart specialisation strategies. To test the hypothesis that these firm-level indicators can characterize the intraregional differences in aggregate performance, the paper sets up a meta-analysis framework between these indicators and structural indicators (employment growth and specialisation index) measured at the NUTS-3 level. For the meta-analysis at this novel intraregional level, the paper exploits the Lombardy region as a case study. Lombardy is well suited for the aims of this paper, being a large and competitive European region, whose territory—as well as its labor market—is highly differentiated, from peripheral and mountainous areas to many medium and small cities, second-tier large cities and a large metropolitan area—the city of Milan. All these territories are characterized by different economic and social vocations, but all share the same regional administration. The results of the meta-analysis show that firm-level indicators correlate with the aggregate performance of regions and that the structural measures selected can characterize different territories in different conditions. Hence, the competitiveness of firms seems to translate into aggregate territorial performance at small spatial scales. This implies that territorial specificities are also relevant inside regions and should be considered in designing regional policy interventions, such as those of the Smart Specialisation Strategy (S3).

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1 Introduction

With the programming period 2014–2020, European Union (EU) Cohesion Policies (CP) introduced the key concept of smart specialisation (Foray, 2015), which further focused EU cohesion policies around the two main elements of innovation and territorial competitiveness, fitting smart specialisation as an ex-ante condition for receiving support from European structural and investment funds (Landabaso, 2014; Mccann & Ortega-Argilés, 2013). A key aspect of these smart specialisation strategies is the centrality of the context in which they are implemented. Indeed, following the growing emphasis gained by place-based policies (Barca et al., 2012), the proposed reforms aim to better link institutions, policies and incentives around and with the territorial context and evolutionary trends of the regions.

Connectedly with the rise of smart specialisation strategies, another concept returned to centrality in the allocation and design of regional policies: territorial competitiveness. Despite being originally conceived as firm-related, the concept of competitiveness has also been applied to analyze territories since the early 1990s (Porter, 1990); due to its direct link with the capacity for production—either at the firm or territorial level—today, the concept of competitiveness is a common element for policy design, especially regarding policy programs aimed at reducing the productivity gaps.

Policies built with these elements at their core are designed and allocated with the intent of nurturing and supporting regions and territories that are best competing in the international market but also to help lagging or underdeveloped regions and territories "in order to build competitive advantage by developing and matching research and innovation" (REGULATION (EU) No 1303/2013 OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL of 17 December 2013, article 2).

Smart specialisation strategies are inherently territorialized, and their main strength is that they aim to improve economic performance and development paths by fostering and exploiting local knowledge and territorial capital. However, when pragmatically observing how these territorial aims can be achieved, a "mismatch" emerges between the allocation and effective implementation of these policies.

Indeed, regional and cohesion policies are commonly allocated at the NUTS-2 level[1]; likewise, most relevant measures and indicators are also aggregated at that level. Most notably, this is the case for the Regional Competitiveness Index (RCI) computed by the EU Commission at the NUTS-2 level accounting for multiple characteristics of a region and its industrial structure into a single measure comparable between regions.

[1] NUTS stands for Nomenclature of Territorial Units for Statistics, it is the hierarchical classification of European territorial units.

On the other hand, these policies are to be implemented at the territorial level unevenly over the regional territory. As abundantly shown by prominent scholars in regional science, a large set of influencing factors are highly territorialized and unevenly distributed in space (e.g., infrastructure, human capital, skilled workers and quality institutions) (Dierickx & Cool, 1989; Maskell & Malmberg, 1999). Moreover, firms and economic activities (both related and nonrelated) are not evenly distributed over the regional territory.

All these elements, commonly called territorial capital (Camagni, 2009; Fratesi & Perucca, 2019), are highly distributed in the regional territory and influence it at a much smaller scale than NUTS-2.

This paper argues that the set of information and instruments available for the allocation and the design of these policies may not match the territorial level on which they take place. Therefore, a different instrument—measuring territorial competitiveness at the subregional level—is needed to better inform the design and implementation of smart specialisation strategies.

By means of a novel methodology and firm-based territorial analyses correlating specialisation, employment growth and territorial competitiveness, this paper aims to show how it is possible to produce subregional measures of territorial competitiveness—exploiting firm-level data—providing territorial information with varying territorial units on which to design these place-based policies.

Focusing on a single NUTS-2 region, the Lombardy region in Italy, the paper first presents how intraregional territorial competitiveness can be measured via firm-level data. Then, a dynamic meta-analysis shows how these measures correlate with specialisation and territorial growth and development.

In its concluding remarks, the paper argues that—as shown by the results of the meta-analysis—this intraregional measure of territorial competitiveness can provide vital territorial information for the design of place-based policies and, in the context of Smart specialisation Strategies (S3) and Regional Cohesion Policies can be a very useful instrument to implement—rather than replace—aggregate indicators such the Regional Competitiveness Index.

2 Smart Specialisation Strategies and Territorial Competitiveness: A Missing Link Between Theory and Practice

2.1 S3 and Territory

In the contemporary EU policy debate, smart specialisation strategies are the central node of many policy programs and designs. Indeed, the agenda resulting from this paradigm-shifting concept was in the programming period 2014–2020 an ex-ante condition for receiving support from EU structural and investment funds in TO1

(Landabaso, 2014) and will remain fundamental in the programming period 2021–2027.

At their core, smart specialisation strategies assume that the context in which firms operate not only matters but can also be the main driver of the technological evolution of innovation systems. Existing strengths but also untapped potentials of territories can be exploited to foster—through these agendas—growth and maximize the development opportunities of territories and regions. Despite the name, the smart specialisation agenda is not intended to encourage sectoral specialisation but rather to foster diversification around a core set of activities and generate new specialties and opportunities for local concentration and agglomeration of resources and competences in these domains' (Foray, 2015 p.1).

From this perspective, the context—with its local knowledge networks, trade links, spillovers and everything else that today is considered a key element of the related variety (Boschma & Iammarino, 2009; Boschma et al., 2012; Frenken et al., 2007; Neffke et al., 2011)—is considered the existing structure on which to develop a 'diversified' specialisation (Grillitsch et al., 2018) and to foster related explorative, research activities (Foray, 2014).

It is important to note that although smart specialisation strategies do not target specific territories and regions, most positive examples of such strategies are located in structurally and economically strong regions (Foray, 2015). It is clear that by heavily relying on locally existing strengths and opportunities, the effectiveness of these strategies is largely impacted by the development path and industrial past of the region. This is where a missing link emerges; while both policy frameworks and policy actors have switched already their perspectives, from a regional to a – smaller – territorial one, there still is a lack of tools and support instruments (such as the European Regional Competitiveness Index, which only considers the regional level) available to a smaller level than the NUTS-2.

2.2 Case Study Description

For every empirical study, defining and selecting a well-suited case study is a key step.

In this case, it is important to select NUTS-3 areas belonging to the same NUTS-2 region because only in this way the institutional framework will be the same for all. At least this is what happens in Italy, the country from which data come from, where NUTS-2 regions are endowed with large autonomy.

We select the most competitive region of the country, Lombardy, which is also the largest in terms of population, territory, and total GDP.[2] The region has just one smart specialisation strategy although it is composed of many different territories

[2] Lombardy not only consistently scores higher than the rest of the country on the RCI (Regional Competitiveness Index) but also holds a higher GDP per capita of €39,200 in 2018, compared to the average of €29,700 in Italy and €31,000 in the EU (Eurostat, 2020).

with their geographical and economic specificities. In particular, this region includes one large metropolitan area the city of Milan as well as medium-sized cities and more peripheral areas both in the plains and in the mountains. Overall, Lombardy holds a large territory and is the most populated region in the country, almost doubling the population of the second largest region with almost 10 Million inhabitants (Istat, 2022).

3 Data and Methodology

3.1 Measuring Territorial Competitiveness Using Firm-Level Data

The competitiveness of territories and that of the companies located within those territories are intrinsically connected. Indeed, the competitive capacity of a particular firm is influenced by three sets of factors: (i) the characteristics of the individual firms; (ii) the dynamics of the industrial sectors; and (iii) a large set of territorial elements and characteristics which, taken together, are called territorial capital.

Exploiting this general assumption, a "two-step" matching design (Rosenbaum & Rubin, 1985) is implemented to isolate the differential effects on the competitiveness of firms produced overall by those elements known as territorial capital (Camagni, 2009; Fratesi & Perucca, 2019). If in fact, two firms in the same industrial sector share similar characteristics—being different only in terms of their location—resulting differences in terms of competitiveness between those firms will be due to the external conditions in which they operate. By aggregating firms based on their location in one of the 12 NUTS-3 provinces inside the Lombardy region, a "two-step" matching design is implemented to separately control for industrial dynamics and individual firm characteristics. The produced differentials can easily be employed to proxy internal differences in territorial competitiveness.

This counterfactual workflow, recently proposed by (Fantechi & Fratesi, 2022), has a number of advantages, especially over the use of composite indices. Indeed, it employs firm-level microdata instead of administrative statistical or census data; the availability of firm-level microdata is constantly growing and, especially for European countries, today several databases are available detailing firms' master and balance information for almost the last two decades. Moreover, the workflow is quite flexible, allowing easy variation in both the level of analysis and the area of study and allowing for both static and dynamic enquiries. Nevertheless, the current formulation of the workflow, despite allowing for a certain degree of freedom and being able to control and isolate from industrial sectorial dynamics and differences in firms' characteristics, is not able to differentiate between the first and second "nature" of territorial capital.

The counterfactual strategy implemented to measure intraregional territorial differences in territorial capital is a “two-step” matching design (Rosenbaum & Rubin, 1985).

Each of the two steps of the strategy is designed to control different influencing factors of firms’ competitiveness and thus isolate the territorial effect. The first step in the matching design consists of an exact match for the industrial sector in which the firms operate. Indeed, the industry in which a specific firm operates is probably the most influential single aspect to account for. Firms operating in different markets may not only have very different production margins, market sizes and organizational requirements but may also differ in terms of growth and dynamic opportunities. The overall effect of being part of different industrial sectors is considered by matching firms sector by sector using the NACE 4-digit classification and the 22 categories following the STAN industry list ISIC rev.4 classification (Horvát & Webb, 2020).

Based on this fine classification of the main industrial sector in which a firm operates, firms are matched, and their performance compared, only with other firms in the same class.

The second step of this matching design is composed of propensity score matching (via a probit function with a caliper of 0.05) to control for past trends and specific firm characteristics. In this second step of the strategy, the aim is to isolate the differentials in firms’ performance—based on the NUTS-3 territory in which they are located—from the influence of specific firms’ characteristics. To do so, the probit function controls our data for several characteristics of firms to only compare firms in each industrial sector only with similar firms (in the same industrial sector) located elsewhere.

Several are the characteristics selected for this operation:

The ***age of the firm*** is accounted for via a discrete variable recording the number of years passed from the registered incorporation of the firm.

Being a ***beneficiary of public policy*** interventions or not is indicated via a dummy that identifies those firms that received some kind of public assistance in the years prior to the research.

Whether firms have a ***cooperative status*** is accounted for with a dummy variable identifying those firms incorporated as cooperatives.

Involvement in international markets is again accounted for with a dummy variable (due to availability of data) identifying those firms who self-report ***export activities***.

Firm size is indicated by a discrete variable recording the number of employees.

The ***reliance on immaterial assets*** by firms is accounted for by means of a continuous variable measuring the share of immaterial assets (over total assets) declared by a specific firm.

Finally, ***financial position*** is accounted for by a continuous variable measuring the ratio of debts to total gross earnings.

All these variables are computed on firm-level, self-reported, yearly data recovered from the AIDA database (Bureau van Dijk, n.d.).

In this way, it is possible to compare firms present in one of the 12 provinces of Lombardy with other firms which belong to the same sector and are structurally similar but are located in a different province. The differentials arising will depend on territorial capital of the provinces.

Three indicators are used as measures of productivity and profitability.

Labor productivity: computed as the ratio between Value Added and number of Employees (Aguiar & Gagnepain, 2017; Bhattacharya & Rath, 2020; Falciola et al., 2020; Laureti & Viviani, 2011; Nemethova et al., 2019).

Total Factor Productivity: computed as the residual of a Solow production function (Solow, 1956) based on Value Added and calculating the capital stock at the firm level using the Perpetual Inventory Method (PIM) (Gal, 2013), thus also including the firm's capitals and capitalization in the computation (Albanese et al., 2020; Ciani, Locatelli, & Pagnini, 2018; Gal, 2013; Lasagni et al., 2015).

Profitability: measured as a ratio of EBITDA on Turnover, also known as ROA, Return On Assets (Aguiar & Gagnepain, 2017; Akimova, 2000; Bharadwaj, 2000; Bramanti & Ricci, 2020).

As a final control, specific to the analyzed case study, the research also accounts for an eventual "sorting effect" in the localization selection by firms. Indeed, large cities, especially large metropolitan areas, are exceptionally more attractive to firms than other territories, producing results—in terms of firms' productivity—often on a different scale. This is due not only to higher stocks of territorial capital but also to being a "place on the map" (i.e., branding opportunities, name recognition) (Wheeler, 2001) and providing unique opportunities. To avoid the possible confusion generated by this sorting effect, a simple restriction is implemented in the matching design to account for this effect without affecting or penalizing firms located in different territories: the province of Milan (which is mostly composed of the metropolitan area of Milan, the only truly "big" city in the region) is compared with the rest of the region to calculate the competitiveness differential for firms of being located there; conversely, when matching firms from the other provinces, firms located in the province of Milan are excluded from the computation.

The time span of the analysis includes a period of ten years, between 2009 and 2019. Two main types of data are required for the analysis: i) firm-level balance sheet data, provided by AIDA (Bureau van Dijk, n.d.); territorial, administrative-level data provided by Istat (15th Italian Census: ISTAT, 2011) and ASIA (National registry of Firms: ISTAT, 2020).

As shown in (Fantechi & Fratesi, 2022), the produced differential can easily and effectively be employed to identify and characterize internal differences in territorial capital. However, this is not the focus and aim of the present paper; the results of the described two-step matching design will indeed serve as input data for a meta-analysis connecting them to structural indicators of specialisation and regional growth and development.

3.2 Meta-Analysis

The final objective of the analysis is to show how the proposed measure of territorial competitiveness—compiled at the intraregional level from firm-level data—correlates to established measures of regional growth and specialisation. Territorial competitiveness plays a key role in today's policy design and implementation and has often been positively correlated with a positive impact on regional growth and development. While this correlation has been shown to exist at the regional level, where territorial competitiveness is measured via composite indicators, this paper wants to show that the same correlation also stays true at the intraregional level. Moreover, by measuring territorial competitiveness as a residual of the firms' competitiveness differential based on their location, the paper also provides a novel—and quite adaptable—methodology to measure territorial competitiveness; showing how this measure of territorial competitiveness correlates with—connected—more established measures of regional growth and specialisation will provide additional data in favor of the use of this indicator and more detailed territorial information on which design more effective cohesion and industrial policies.

While the analysis per se—consisting of a set of multiple regressions—is quite straightforward, it is worth describing in more detail both the selection of indicators and the data operations prior to inputting them into the models.

3.3 Specialisation Indicators and Data Preparation

To correlate the competitiveness of territories inside a specific NUTS-2 to their territorial growth and development, a viable measure of growth at the NUTS-3 level must be identified. Territorial growth, which is commonly measured at the NUTS-2 level, is a complex concept encompassing various dimensions from individual well-being, social inclusion, economic prosperity, and structure to access to services and institutions. Many of the metrics employed are directly recorded or measured from national and supra-national statistical offices, mostly at the NUTS-2 level. Considering the scarcity of such measurements at the NUTS-3 level and that the aims of this paper are directly connected to the specific dimension of territorial economic prosperity, only one measure of territorial growth has been selected: employment growth. Differently from GVA, this variable is able to account for the territorial effects of economic aspects in a way which also considers its social consequences, in terms of employment (Fratesi & Rodriguez-pose, 2016).

For this analysis, the growth in employment is measured as the relative change between 2007 and 2019; this is possible thanks to data from ASIA (The Italian registry of active firms) reporting the total number of employed workers in each industrial sector at the municipal level.

The relative change in employment is calculated for each Nace 2-Digit division (aggregating less relevant and numerous sectors) at the NUTS-3 provincial level for the whole region. The same unit of analysis is also employed for the computation of differential.

Finally, output data—from the analysis of territorial competitiveness performed employing firm-level data—need to be processed before imputing them into the model.

As described in the first part of the methodological paragraph, territorial competitiveness is measured via firm-level data producing territorial competitiveness differentials for each of the analyzed territories.

To improve the reliability and explanatory power of the meta-analysis, output data are processed and discretized before imputing them. Indeed, it is important to consider that the produced counterfactual results—which, after being processed, will become input data for the meta-analysis—are normalized territorial differentials coefficients of competitiveness measured via firm-related data. The paper is interested in the territorial-level relationship between the differences in competitiveness detected by the counterfactual strategy and different territorial trends in terms of employment growth. Directly imputing the coefficients in the models would not provide additional information on this relationship, while at the same time, it would produce a much more complicated and less reliable model. For this reason, before imputing, each coefficient has been discretized taking one of three possible values: (1) "Not significant" for those coefficients which are, regardless of the sign, not statistically significant; (2) "Positive" for those coefficients which are both positive in sign and statistically significant; (3) "Negative" for those coefficients which are both negative in sign and statistically significant.

Additional controls are included in the analysis to provide more robustness to the results. Both industrial sector controls and spatial controls (NUTS-3 level) are included; moreover, "specialized", and "nonspecialized" territories are identified before computing the analysis: for each observation, a specific industrial sector in a specific province (NUTS-3), we identified whether it is "more specialized than average" or "less specialized than average" by exploiting sectoral employment location quotients.

4 Results and Discussion

With the aim of bridging the gap between existing structural indicators of territorial (regional) competitiveness and the need for more territorialized measures of competitiveness to inform the design and implementation of policies, the paper presented—following (Fantechi & Fratesi, 2022)—a counterfactual workflow to measure differentials of territorial competitiveness at the subregional level.

This is done by employing firm-level data with a 2-step matching strategy: the first step eliminates the heterogeneity produced by firms being part of different industrial sectors with an exact match, ensuring that firms operating in a specific sector are only matched and compared with firms in the same exact sector. With propensity score matching over individual firms' characteristics, the second step controls for the different conditions in which the firm operates (e.g., size, initial production capacity, different assets reliance, financial position) so that firms are only compared to similar firms located elsewhere. As argued in (Fantechi & Fratesi, 2022), the produced differentials are indicators of differences in territorial competitiveness produced by the different distribution and availability of territorial capital inside the region.

The main aim of this paper is, then, to show and test the correlation between the produced differentials and established measures of territorial competitiveness measured at the same territorial level.

Before inputting data for the meta-analysis, firm-level territorial differentials produced with the counterfactual strategy are processed and discretized as discussed in the previous section. ATTs from all three indicators (labor productivity, total factor productivity and profitability) are calculated and inputted, measuring three different—and connected—sides of the competitiveness of firms, both in static form and dynamic one (for a total of six indicators).

The meta-analysis is performed by means of multiple linear regressions on the change in employment. Figure 1 reports the results of such meta-analysis where each indicator takes value "1" if the specific computed differential is statistically significant and positive and 0 otherwise (significant and negative, or not significant). This is done to both provide a more readable output and simplify the analysis to better show the correlation between change in employment and the computed differentials.

Figure 1 shows a number of interesting results concerning the regional specialisation and especially the openness indicators. The table is organized in columns with different regression models where alternative specifications are presented.

CANGHE IN EMPLOYMENT	(1) Specialization Only	(2) Static Only	(3) Dynamic Only	(4) Both	(5) NUTS-3 Controls	(6) No Milan	(7) Specialized Only	(8) Specialized and Average	(9) Not Specialized and Average	(10) Not Specialized Only
Specialization										
More than Average	**-0.0442***	**-0.0433***	**-0.0508****	**-0.0504****	**-0.0422***	**-0.0548****		**-0.0512****		
	(0.0239)	(0.0229)	(0.0242)	(0.0236)	(0.0247)	(0.0242)		(0.0236)		
Less than Average	-0.0103	-0.00858	-0.0157	-0.0162	-0.00541	-0.0182			-0.0228	
	(0.0241)	(0.0234)	(0.0257)	(0.0253)	(0.0263)	(0.0267)			(0.0260)	
Static indicators										
Positive ATT Labor Prod		**0.0721^**		**0.0650^**	**0.0642^**	**0.0833^**	0.0505	**0.0809^**	0.0607	-0.0341
		(0.0455)		(0.0445)	(0.0454)	(0.0615)	(0.0558)	(0.0540)	(0.0575)	(0.0601)
Positive ATT TFP		-0.00345		0.00927	0.0177	0.0252	0.00719	0.00280	0.00664	0.0218
		(0.0201)		(0.0187)	(0.0242)	(0.0238)	(0.0549)	(0.0205)	(0.0211)	(0.0395)
Positive ATT ROA		0.00394		0.00410	0.00597	0.00402	0.0678	-0.00530	-0.00547	0.0175
		(0.0187)		(0.0189)	(0.0205)	(0.0195)	(0.0769)	(0.0252)	(0.0207)	(0.0344)
Dynamic indicators										
Positive ATT Labor Prod			0.00416	-0.00213	-0.000631	-0.00783	0.0209	0.0227	-0.0140	**-0.148****
			(0.0264)	(0.0280)	(0.0269)	(0.0286)	(0.109)	(0.0278)	(0.0298)	(0.0666)
Positive ATT TFP			**0.0580*****	**0.0481****	**0.0520****	**0.0554***	**0.0972***	**0.0654*****	0.0185	0.0171
			(0.0223)	(0.0230)	(0.0250)	(0.0304)	(0.0554)	(0.0214)	(0.0302)	(0.0953)
Positive ATT ROA			**0.0995***	**0.101***	**0.0971***	**0.103***	0.0928	**0.121^**	**0.103^**	**0.101***
			(0.0594)	(0.0572)	(0.0543)	(0.0571)	(0.101)	(0.0799)	(0.0710)	(0.0575)
Nace Sector Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Constant	0.0366	0.0295	0.0321	0.0265	-0.0105	0.0256	-0.0593	0.0303	0.0545	-0.0165
	(0.0579)	(0.0590)	(0.0567)	(0.0582)	(0.0701)	(0.0643)	(0.0447)	(0.0918)	(0.0818)	(0.0239)
Observations	260	260	260	260	260	238	54	183	206	77
R-squared	0.476	0.492	0.506	0.519	0.547	0.527	0.684	0.574	0.520	0.583

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1, ^ p<0.15

Fig. 1 Meta-analysis results *Source* Authors' own elaboration

The left side of the table presents relations with the full sample and first shows that territories with higher than the average specialisation in their industries have produced a worse performance in terms of employment.

On the contrary, these territories where firms are more competitive than their counterparts, usually have a significantly better performance. This is true in particular for the indicator of total factor productivity; this is the most significant coefficient and shows that in those places where firms are more innovative, additional jobs are created.

As expected, there is also a positive coefficient for labor productivity showing that where labor is more productive, the firms of these territories react by hiring additional workers.

There is however a third result which is somehow counterintuitive. When firms increase their profitability then they also create jobs. This is demonstrated by the positive and significant coefficient of ROA. At least in these advanced regions, the profitability of firms is not in contrast with the creation of jobs, and the most competitive firms are usually innovative so that they produce returns for their investors and at the same time additional work for their local communities.

The right part of the table presents results for regressions on different sub-samples to see if the effects detected depend on specialisation.

It shows that the positive impact of total factor productivity is mostly present in areas of specialisation. The positive effect of profitability is instead present in all areas but the most specialised.

5 Conclusions and Further Research

In this paper, we identified a ‘missing link’ between the level at which smart specialisation programs are assigned and designed and the level at which they are applied. The key element in building this research is indeed the mismatch between the availability of tools and instruments for policy programming and design and the territories in which the policies are to be implemented.

Focusing on territorial competitiveness—central element and aim of Smart specialisation Strategies—this missing link is evident: tools, indicators, and indices of territorial competitiveness (especially those produced by EU’s institutions) provide information at the regional (NUTS-2) level; in order to maximize both the efficiency of policy design and the effectiveness of policy implementation, Smart Specialisation Strategies can greatly benefit from more territorialized measures and indicators of territorial competitiveness. In a recent publication, Fantechi and Fratesi (2022) developed an adaptive framework to measure differentials of territorial competitiveness inside a region. This framework, presented in Sect. 3 of this paper, employs firm-level data to provide territorialized firms’ competitiveness indicators by isolating and controlling the effects of industrial sectorial dynamics and firms’ individual characteristics. According to the authors, the main feat of the framework is its adaptability to different levels of analysis, being smaller administrative units (as performed for the analysis in this paper) or specific geographical areas. Information provided with this framework is not intended to replace existing indicators and indices of territorial competitiveness; rather, to implement them with information they are not able to provide to help the design and implementation of smart specialisation strategies.

The main result of this article was to show the relation between these territorialized firms' competitiveness measures, specialisation, and territorial growth (growth in employment) to test and validate the indicators as a valuable tool to measure subregional differentials of territorial competitiveness and performance.

Following the outlined framework, multiple territorialized firms' competitiveness indicators of both productivity and profitability of firms are computed at the provincial (NUT-3) administrative level. The results provided in this paper show the interesting potential of this tool. One main result is that positive territorialized differentials of productivity (TFP) and profitability (ROA) correlate positively with larger local growth in employment over the same period. Interestingly, the third selected indicator of territorialized firms' competitiveness, labor productivity, shows a lower correlation.

Taken together, these results show that the proposed framework can help individuate increasingly competitive territories inside the region and can also provide an indication of which elements of firms' competitiveness local territories are able to provide better support to local employment growth.

The territorial-level relation between firms' competitiveness—through their territorialized indicators—and the growth in employment shows the possible relevance of the framework developed by Fantechi and Fratesi (2022), not only as a research tool but also as a tool for policy design providing relevant information on the competitiveness of territories inside a region.

The limits and shortcomings of this approach are multiple and represent the main reason why the proposed framework is not intended to replace existing measures and indicators but, rather, to integrate them. Some of these limits are inevitable due to the framework itself; the produced territorialized firms' competitiveness indicators are territorial differentially produced with a counterfactual 2-step matching, meaning that they are relative measures rather than absolute. They correctly represent internal territorial differences, but to provide a correct interpretation, they are related to the overall context and dynamics of the region; results emerging from this analysis cannot be generalized and directly applied to other European regions without considering the relevance and specificities of different regional dynamics and characteristics. Finally, other smaller limits are due to the availability of data and information, specifically firm-level data; firm-level balance sheet data available today are, despite being a great resource, still partially lacking in precision and completeness. This clearly represents a limitation to this study (as well as other studies employing the same data) but a limitation that is destined to fade in the coming years as the database becomes more complete and the capacity for data gathering and production refines.

References

Aguiar, L., & Gagnepain, P. (2017). European cooperative R&D and firm performance: Evidence based on funding differences in key actions. *International Journal of Industrial Organization, 53*, 1–31. https://doi.org/10.1016/j.ijindorg.2016.12.007

Akimova, I. (2000). Development of market orientation and competitiveness of Ukrainian firms. *European Journal of Marketing, 34*(9/10), 1128–1148. https://doi.org/10.1108/03090560010342511

Albanese, G., de Blasio, G., & Locatelli, A. (2020). Does EU regional policy promote local TFP growth? Evidence from the Italian Mezzogiorno. Papers in Regional Science, 0–3,. https://doi.org/10.1111/pirs.12574

Barca, F., Mccann, P., & Rodríguez-Pose, A. (2012). The case for regional development intervention: Place-based versus place-neutral approaches. *Journal of Regional Science, 52*(1), 134–152. https://doi.org/10.1111/j.1467-9787.2011.00756.x

Bharadwaj, A. S. (2000). A resource-based perspective on information technology capability and firm performance: An empirical investigation. *MIS Quarterly: Management Information Systems, 24*(1), 169–193. https://doi.org/10.2307/3250983

Bhattacharya, P., & Rath, B. N. (2020). Innovation and firm-level labour productivity: A comparison of Chinese and Indian manufacturing based on enterprise surveys. *Science, Technology and Society, 25*(3), 465–481. https://doi.org/10.1177/0971721820912902

Boschma, R., & Iammarino, S. (2009). Related variety, trade linkages, and regional growth in Italy. *Economic Geography, 85*(3), 289–311. https://doi.org/10.1111/j.1944-8287.2009.01034.x

Boschma, R., Minondo, A., & Navarro, M. (2012). Related variety and regional growth in Spain*. *Papers in Regional Science, 91*(2), 241–256. https://doi.org/10.1111/J.1435-5957.2011.00387.X

Bramanti, A., & Ricci, S. (2020). Structure and performance of the Italian alpine "core": A counterfactual analysis. *Worldwide Hospitality and Tourism Themes*. https://doi.org/10.1108/WHATT-05-2020-0026

Camagni, R. (2009). Territorial capital and regional development. In R. Capello & P. Nijkamp (Eds.), *Handbook of Regional Growth and Development Theories* (pp. 118–132). Edward Elgar.

Ciani, E., Locatelli, A., & Pagnini, M. (2018). Evoluzione territoriale della TFP: analisi dei dati delle società di capitali manifatturiere tra il 1995 e il 2015 (Questioni di Economia e Finanza).

Dierickx, I., & Cool, K. (1989). Asset stock accumulation and sustainability of competitive advantage. *Management Science, 35*(12), 1504–1511. https://doi.org/10.1287/mnsc.35.12.1504

Eurostat. (2020). Regional Innovation Monitor.

Falciola, J., Jansen, M., & Rollo, V. (2020). Defining firm competitiveness: A multidimensional framework. *World Development, 129*, 104857. https://doi.org/10.1016/j.worlddev.2019.104857

Fantechi, F., & Fratesi, U. (2022). Measuring competitiveness differentials inside the same region: A propensity-score matching approach. *Social Indicators Research*, 1–27. https://doi.org/10.1007/s11205-022-02908-7

Foray, D. (2015). *Smart specialisation: Opportunities and challenges for regional innovation policy*. Routledge.

Foray, D. (2014). Smart specialisation. *Smart Specialization* (December). https://doi.org/10.4324/9781315773063

Fratesi, U., & Rodriguez-pose, A. (2016). The crisis and regional employment in Europe. Working Paper, pp. 33–57.

Fratesi, U., & Perucca, G. (2019). EU regional development policy and territorial capital: A systemic approach. *Papers in Regional Science, 98*(1), 265–281. https://doi.org/10.1111/pirs.12360

Frenken, K., Van Oort, F., & Verburg, T. (2007). Related variety, unrelated variety and regional economic growth. *Regional Studies, 41*(5), 685–697. https://doi.org/10.1080/00343400601120296

Gal, P. N. (2013). Measuring Total Factor Productivity at the Firm Level using OECD-ORBIS Recent. OECD Economics Department Working Papers (1049), 1–59.

Grillitsch, M., Asheim, B., & Trippl, M. (2018). Unrelated knowledge combinations: The unexplored potential for regional industrial path development. *Cambridge Journal of Regions, Economy and Society, 11*(2), 257–274. https://doi.org/10.1093/CJRES/RSY012

Horvát, P., & Webb, C. (2020). The OECD STAN Database for industrial analysis: Sources and methods. OECD Science, Technology and Industry Working Papers, OECD Publishing, Paris, 2020/10. https://doi.org/10.1787/ece98fd3-en

ISTAT. (2011). 15° Censimento della popolazione e delle abitazioni 2011. Retrieved from www.istat.it

ISTAT. (2020). Registro statistico delle imprese attive (ASIA). Retrieved from www.istat.it

ISTAT. (2022). Censimento permanente. Retrived from www.istat.it

Landabaso, M. (2014). Guest editorial on research and innovation strategies for smart specialisation in Europe. *European Journal of Innovation Management, 17*(4), 378–389. https://doi.org/10.1108/EJIM-08-2014-0093

Lasagni, A., Nifo, A., & Vecchione, G. (2015). Firm productivity and institutional quality: Evidence from italian industry. *Journal of Regional Science, 55*(5), 774–800. https://doi.org/10.1111/jors.12203

Laureti, T., & Viviani, A. (2011). Competitiveness and productivity: A case study of Italian firms. *Applied Economics, 43*(20), 2615–2625. https://doi.org/10.1080/00036840903357439

Maskell, P., & Malmberg, A. (1999). The competitiveness of firms and regions. "Ubiquitification" and the importance of localized learning. *European Urban and Regional Studies*, *6*(1), 9–25. https://doi.org/10.1177/096977649900600102

Mccann, P., & Ortega-Argilés, R. (2013). Regional studies smart specialisation, regional growth and applications to european union cohesion. *Policy*. https://doi.org/10.1080/00343404.2013.799769

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. https://doi.org/10.1111/j.1944-8287.2011.01121.x

Nemethova, V., Siranova, M., & Sipikal, M. (2019). Public support for firms in lagging regions-evaluation of innovation subsidy in Slovakia. *Science and Public Policy, 46*(2), 173–183. https://doi.org/10.1093/scipol/scy046

Porter, M. E. (1990). The competitive advantage of nations. *Harvard Business Review*, *68*, 73–93.

Rosenbaum, P. R., & Rubin, D. B. (1985). Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. *The American Statistician, 39*(1), 33–38. https://doi.org/10.1080/00031305.1985.10479383

Solow, R. M. (1956). A contribution to the theory of economic growth. *Quarterly Journal of Economics*, *70*(1), 65–94. Retrieved from http://qje.oxfordjournals.org/content/70/1/65.short

van Dijk, B. (n.d.). Balance sheet data for Italian Firms. AIDA.

Wheeler, C. H. (2001). Search, sorting, and urban agglomeration. *Journal of Labor Economics, 19*(4), 879–899. https://doi.org/10.1086/322823

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