The New Economics of Positioning
places as knowledge platforms

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Contents

to Roberto Camagni
who has just left us, but his work continues and will continue to inspire us.

1. Introduction

This work is positioned within the geography of innovation strand that emphasizes the role of localized knowledge spillovers. This literature is contributing to the identification of the specific channels through which knowledge spillovers flow through different forms of space. It is a well-established finding in the Evolutionary Economic Geography literature that different types of proximity foster innovation (Boschma, 2005). These different proximities correspond to different forms of space: physical, institutional, organizational, social and cognitive. Capello (2015) categorizes the different types of space into physical-metric, uniform-abstracted, diversified-relational, diversified-stylized.

In economic terms, space is the manifestation in multiple connected places of the benefits of agglomeration processes (Bellanca, 2021). In economic theory, agglomeration economies enclose the spatial forms of increasing returns. These are substantiated by the advantages of sharing, matching and learning (Duranton and Puga, 2004). These competitive advantages can benefit firms in the same sector (Marshall-Arrow-Romer externalities), those in different sectors (Jacobs) and finally those in competition with each other (Porter). These give rise to economies of scale (internal to the firm), localization (internal to industry), urbanization (internal to a geographic area) and district (specific to a local system). This scheme of explanation rests on a precise theoretical idea: at various levels of abstraction, economic systems are formed that are embedded in larger economic environments, and some economic benefits may flow out of one environment into another. These externalities (or external economies) do not presuppose a physical space since an abstract space is sufficient to realize them (Bellanca, 2021).

The development of the empirical principle of relatedness (Hidalgo et al., 2007, Hidalgo et al., 2018), according to which the probability of a place entering (or leaving) an economic activity is a function of the number of related activities present in that place, is pushing a growing literature to unpacking the different channels through which knowledge flows. This instrument can also be applied to places, and the geographies they form, based on different forms of space besides the physical. Proximity measures have been used to investigate product space (Hidalgo *et al.,* 2007), industry space (Neffke, *et al.,* 2011; Neffke & Henning, 2013), technology space (Rigby, 2015; Boschma *et al.,* 2015), occupation space (Muneepeerakul *et al.,* 2013; Alabdulkareem *et al.,* 2018), research space (Guevara *et al.,* 2016; Chinazzi *et al*., 2019), music space (Klement & Strambach, 2016), and cultural consumption (Lizardo, 2018). From this perspective, the right positioning with respect to location and related spaces becomes critical to economic performance.

The concept of positioning used to describe the benefits that reside in different spatial forms is widely found in literatures of, just to name the closest ones, Regional Economics (Bergman and Maier, 2008), Global Value Chains (van der Marel, 2015), marketing (Brooksbank, 1994), management (Lefebvre and Lefebvre, 1993) and innovative eco-systems (Valkokari *et al*., 2017).

This work introduces in this literature the concept of positioning economies which are based on the ability to be positioned in different physical and nonphysical spaces to seize the benefits from different forms of knowledge.

Places are thus conceived as platforms that connect knowledge across different dimensions of space. This concept is used in the next three chapters to study different forms of spillover that cross physical, institutional, cognitive, relational, functional, hierarchical and symbolic spaces.

The first chapter reviews the traditional innovation literature dealing with the relationship between market structures, technological and geographic space in promoting innovation. A large body of literature has studied which form of market was best suited to promote innovation, with mixed results leading to the emergence of the so-called innovation puzzle. The literature on the evolutionary economics of innovation has helped solve the puzzle through the identification of different innovation regimes based on technological characteristics. Thanks to the concept of relatedness, it is possible to consider these properties of knowledge in relation to place. In fact, the relationship between localized externalities and innovation is mediated by the degree of relatedness between the two, which constrains the flow of knowledge. From this perspective, a framework is proposed that jointly analyzes the characteristics of knowledge and spatial dynamics. This framework can help provide new insights into the innovation puzzle by helping to disentangle four different patterns of innovation in geographic and technological space based on the characteristics of knowledge and its relationship to the knowledge bases of places.

The second chapter analyzes the relational proximity of Italian local labor systems through their positioning in input-output flows at different spatial scale. By applying the methodologies of Economic Complexity, backward (input-related) and forward (output-related) complexity are defined and used to study their contribution to productivity and GDP level of Italian local labor systems. In addition, using the Leontief's procedure, value added activated by final demand localized at different geographic scales is decomposed to measure the contribution of multilevel regional linkages and Global Value Chain participation. The results show that: i. forward complexity has a similar ability to explain variance in GDP per capita and productivity levels as the employment complexity; ii. Intra-regional, inter-regional and international capabilities appear to contribute to GDP per capita and productivity levels in ways specific to the degree of development; iii. both forward and backward complexity contribute to productivity growth, and more markedly to the growth of knowledge-intensive sectors, for SLLs with sufficient absorptive capacity. From a policy perspective, it follows that anchoring and positioning on multiscalar networks must be aligned with local absorptive capacities and degree of development.

The third chapter analyzes how knowledge flows in the hierarchical and symbolic space of Italian provinces and regions through the analysis of the externalities of place narratives. This work proposes a new interpretation of place brand as a Multilevel Threshold Public Good (MTPG) produced by the interaction of narratives from different geographical levels. Using an original dataset of Google trends and tweets from Italian provinces and regions, we test the hypothesis that place branding has a multilevel structure. We further test the MTPG framework applied to place branding, showing that place branding is influenced by different geographic levels which can trigger a spillover in terms of attractiveness if they contribute to crossing a threshold point. The results confirm the presence of a provision point in place branding, showing that the proposed MTPG framework fits the phenomenon. This article contributes to the literature on place branding and brands by providing a new lens for interpreting the phenomenon, which may be useful in better understanding and measuring the interaction of branding strategies operating at different spatial scales.

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2.

Innovation and imitation

A framework in technological and geographical space

This article reviews the traditional innovation literature dealing with the relationship between market structures, technological regimes, and innovation through the lens of the emerging literature on the geography of innovation that focuses on the geographic dimension. A large body of literature has studied which form of market was best suited to promote innovation, with mixed results leading to the emergence of the so-called innovation puzzle. The literature on the evolutionary economics of innovation has helped solve the puzzle through the identification of different innovation regimes based on technological characteristics. Thanks to the concept of relatedness, it is possible to consider these properties of knowledge in relation to place. In fact, the relationship between localized externalities and innovation is mediated by the degree of relatedness between the two, which constrains the flow of knowledge. From this perspective, a framework is proposed that jointly analyzes the characteristics of knowledge and spatial dynamics. This framework can help provide new insights into the innovation puzzle by helping to disentangle four different patterns of innovation in geographic and technological space based on the characteristics of knowledge and its relationship to the knowledge bases of places.

Keywords: Geography of innovation, technological regime, spatial patterns of innovation, relatedness.

1. Introduction

This paper reviews the traditional innovation literatures concerned with the relationship between market structures, technological regimes and innovation through the lens of the emerging geography of innovation literature that focuses on the geographic dimension. With few exceptions, the literature that simultaneously analyzes technological and geographic aspects of innovation is still underdeveloped.

A large body of literature has investigated which form of market was best suited to foster innovation, with mixed results leading to the emergence of the so-called innovation puzzle. At the same time, the evolutionary innovation strand pointed out that this puzzle can be solved through the identification of different technological regimes based on technological characteristics in terms of appropriability, cumulativeness, specificity and technological opportunity (Breschi *et al.,* 2000). Specifically, these characteristics compose two innovation patterns: Schumpeter Mark I, or widening pattern, characterized by frequent innovation, low concentration of innovators, high entry rate and small firms; Schumpeter Mark II, or deepening pattern, characterized instead by high stability of entry rates, high concentration of innovators and markets and large corporations.

While these approaches have put the focus on the characteristics of the technology and its specificity, they have considered these characteristics as absolute, failing in explaining the highly geographic nature of innovation. Hidalgo (2020) with the concept of non-fungibility emphasizes how the qualities of knowledge are relative and, as with the letters of the alphabet, change according to the different associations that are formed. The empirical principle of relatedness measures precisely the affinity between a given technology (sector or product) and a specific place in terms of the mix of technologies present. Put another way, relatedness shows us how technology spillovers can be seized through different types of proximity (physical, cognitive, organizational) and across different spatial scales (local, regional, national, global). To capture this relational aspect and embrace the complexity of the phenomenon, it is necessary to shift the focus to the interaction between technological and spatial dimensions. Even in the literature of the geography of innovation, technological aspects, with few exceptions (Diodato & Morrison, 2019), are little explored. In fact, the emerging strand of the geography of innovation emphasizes how knowledge is spatially concentrated and follows not only path-dependent but also place-dependent dynamics. As Gao et al. (2021) argue, the technological and spatial spheres cannot be kept separate. It is therefore necessary to study the different ways in which different types of knowledge (scientific, embedded in goods, firms, and people) interact with space.

After reviewing the main strands of literature, a theoretical framework capable of holding together technological, institutional, and spatial aspects is proposed in 2 steps: in technological space (step 1), and in technological and together geographical space (step 2). This framework will show 4 different patterns based on the interaction between innovation rent (defined on the basis of the characteristics of cumulativeness, and technological opportunity) and imitation rent (in terms of nonrivalry, relatedness, and appropriability. Finally, in section 5, conclusions are presented.

2. Literature review

The nature of knowledge

A famous article by Kenneth Arrow (1962) supported the idea that "innovation is a public good." According to Romer (1992) most ideas of economic significance are nonrival and at least partially excludable. Although non-rivalry and appropriability are correlated in practice, from a theoretical point of view it is necessary to distinguish between these two aspects because they have very different economic implications (Romer, 1992). In fact, the extent of rivalry is determined entirely by the technology. In contrast, the notion of excludability is determined by both the technology and the legal institutions in a particular economy (Romer, p.13, 1990). The non-rivalry of a good means that potentially that good can be used infinitely many times without reducing the consumption of others. This almost "infinite expansibility" (David, 1993) translates into a marginal cost equal to zero or below the equilibrium price in the case of non-pure non-rivalry good. When the good is used as an input to produce another good a higher level of non-rivalry translates into a greater potential for diffusion of that good. In other words, the non-rivalry of the good is the necessary but not sufficient condition for the externalities produced by knowledge to spread over a wider number of subjects and sectors. Non-rivalry is a prerequisite for its reproducibility and increases the possibility of accumulation. For this reason, it can generate path-dependence and lock-in. The ability to capture these externalities depends on a number of costly factors: knowledge base (absorptive capacity), presence of networks, different dimensions of proximity (Boschma, 2005). In another words, the acquisition of technological knowledge requires some dedicated resources. Technological knowledge spills in the atmosphere, but is use entails some costs (Antonelli, p.3, 2007). In addition, the non-rivalry of a good can differ according to its purpose. The literature differentiates between non-rivalry in use and non-rivalry in exchange (Antonelli, 2007). The former is necessary for both knowledge diffusion and accumulation. The second occurs when knowledge externalities erode a monopoly rent position. Rivalry in exchange limits diffusion but not accumulation.

For Lundvall (2016), knowledge has a degree of rivalry, as the knowledge base is fragmented and, in this way, limits its reproducibility: "*As we shall see, reality is complex and most knowledge is neither completely public nor completely private. The knowledge base is fragmented and may best be illustrated as constituted by a number of semi-public 'pools' to which access is shared regionally, professionally and through networking*" (Lundvall 2016, pp. 135-136). Innovation is a process of collective learning (Lundvall & Johnson 1994; Lawson & Lorenz 1998) through which fragments of knowledge are recombined in new and original ways (Levinthal, 1998). Collective learning is also a club good (Capello, 1999) which has low rivalry but high excludability. Innovative places and spaces are characterized by high localized positive externalities and high costs of access in terms of learning, networking and location costs. The strengthening and expansion of local and international networks, within sectors and between sectors (public, private and university), allow both a greater amount of externality to flow and a higher number of subjects to appropriate these club-based externalities. These club goods can have both market structure: hierarchy (firm) or market-competition (i.e., networks, GVCs, platforms). Both structure hierarchy and market-competition can be characterized by low-rivalry and high excludability (Bolton and Dewatripont, 1994). And organizational and cognitive proximity can facilitate the flow of knowledge within of the firm and the network, respectively (Boschma, 2005).

These specific characteristics of knowledge gave rise to the concept of specificity. Some works on innovation have focused on the specificity of different forms of knowledge (Samarra and Biggiero, 2008; Breschi *et al*., 2000), while others on differentiation of the benefits of a public good into subgroups with different levels of benefits (Antonelli, 2000). Bellandi (2006) have proposed the concept of "specific" public goods. He distinguishes between the private costs of financing the public good and the spatial, technological or organizational costs required to access it. The former takes the form of taxes, tolls, tariffs, etc. The latter depend on the peculiarities and indivisibilities of the public good that are combined with demand differentiation, which make it easier to access the good from certain places and/or for agents who possess certain qualities of connection. Bellandi (2021) calls the former " costs of funding" (private) and the latter "costs of accessing" (private) to the public good. Hidalgo (2020) suggests that specificity is not a universal feature of knowledge but is embodied in the relationship between different types of knowledge. The non-fungibility of knowledge A (e.g., textile production) may be different in relation to different types of knowledge such as B (e.g., fashion) and C (e.g., gardening). This implies that knowledge cannot simply be aggregated or disaggregated, even if we divide it among different (or specific) types. In Hidalgo's (2020) metaphor, knowledge is an alphabet in which different letters can either generate a word or be useless: *"In a world where knowledge is not fungible, economies do not jump from log to camp, but from log to goal"*. This characteristic of knowledge allows us to explain some facts such as its stickiness, especially for more complex economic activities (Balland and Rigby, 2017; Balland *et al*., 2020). Because knowledge is not fungible, economies evolve through path-dependent dynamics. The result is an intricate structure in which development patterns are constrained by the cognitive correlation of activities. The intricate structures observed in the networks of similar products, industries, technologies, and occupations are compelling evidence of this intuition (Hidalgo, 2020). This idea was translated into the principle of relatedness (Hidalgo et al., 2007, Hidalgo et al., 2018), which measure the overall affinity between a specific activity and a location, and empirically verified through a growing literature. The use of the relatedness indicator makes it possible to measure the cognitive proximity between a type of knowledge and a specific location (understood in its economic specialization) and thus know through which channels the non-rivalry of a good will take the form of technological spillovers.

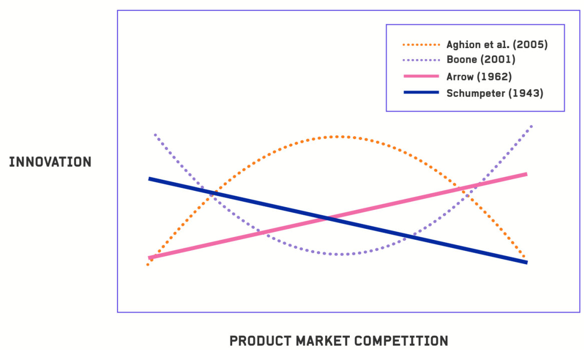
Innovation puzzle

Arrow's idea that knowledge is public (1962) and Romer's related ones (1992) about partial excludability gave rise to two completely opposite lines of research: according to the first (Schumpeterian effect), innovation cannot be provided by markets without government intervention (direct or indirect). The intuitive argument behind the Schumpeterian hypothesis is that ideas are expensive to produce, yet, because of their nonrivalrous nature, they can be (almost) freely appropriated and reproduced by competitors (Aghion and Howitt, 1992). Therefore, the intellectual property rights system is necessary: patents make innovations excludable, thus ensuring at least a second-best outcome (Gilbert and Shapiro, 1990). This approach was elaborated in the industrial organization literature and later incorporated into the New Growth Theory beginning in the late 1980s. Standard IO theory predicts that innovation decreases with competition, as more competition reduces monopoly rents that reward successful innovators. However, empirical works such as Nickell (1996) and Blundell, Griffith & Van Reenen (1999) have found a positive correlation between product market competition and innovative output. Different theoretical approaches have been used in an attempt to reconcile the Schumpeterian paradigm with the evidence provided by these studies, generating different predictions about the shape of the relationship between PMC and innovation. New growth theory predicts a trade-off between "static efficiency," achievable under free competition, and "dynamic efficiency," due to technological progress driven by patented innovations aimed at monopoly acquisition.

The idea that intellectual monopoly is a "necessary evil" for generating innovation and thus economic growth has been challenged by Boldrin and Levine (2008). They depart from the standard assumption that innovation is a public good that can be easily copied at (almost) zero cost. Instead, they argue that " *ideas have value only insofar as they are embodied in goods or people, and that there is no economic justification for the common assumption that ideas are transmitted through costless spillovers*". This second line of research (PMC) challenges two key technological assumptions of the Schumpeterian paradigm: (i) the private fixed costs of innovation are "large"; (ii) imitation is simple and cheap. The idea that competition positively affects technological progress dates back to Adam Smith and is based on the belief that competitive pressure leads to cost reduction, adoption of efficient production methods, and a generally higher rate of innovation. Boldrin et al. (2011) hypothesized that competition fosters innovation and economic progress because new ideas can be fully embodied (embodiment hypothesis) in both an object and human capital. This is the fundamental fact that allows innovators to be rewarded for their inventions even in the absence of intellectual property. Competitive innovation theory is based on the dual assumptions that: (i) inventors have control over their inventions and will require adequate payment to make them available to others, and (ii) imitation is always and everywhere costly because it requires the production or acquisition of the material object or human capital that embodies the innovation.

In recent years, a mixed position has emerged that seeks to reconcile the Schumpeterian theoretical framework with the growing evidence from the competition literature. The model defined by Aghion *et al*. (2005) shows that the relationship between innovation and competition can take the form of an inverted U. In industries where incumbents adopt similar technologies and are equally efficient ("neck-and-neck" industries), competition can increase the incremental profit from innovation and thus encourage investment in R&D (competition flight effect). On the other hand, in unleveled sectors, increased competition may reduce innovation by cumulative and path-dependent benefits (Schumpeterian effect). The U-turn results from the fact that the fraction of leveled and unleveled industries is endogenously determined by equilibrium innovation intensities. They show that when competition is low, a larger fraction of industries at equilibrium involves competing incumbents, so overall the competition effect is more likely to dominate the Schumpeterian effect. On the other hand, when competition is high, the Schumpeterian effect is more likely to dominate. Other empirical work shows diametrically opposite results (Im *et al*., 2015). The results of this literature highlight that the competition/monopoly dichotomy is unable to explain different innovation patterns. Solving this puzzle requires a detailed analysis of the specific nature of technological goods and innovation processes.

Fig 1: The innovation puzzle (from Im et al., 2016)



Evolutionary innovation

Breschi and Malerba (1997) provided some simple examples of the geographical boundaries of industry systems, considering the relevant dimensions of technological regimes. Breschi et al. (2000) believe that the specific pattern of innovative activity of an industry can be explained as the result of different technological (learning) regimes. A technological regime is defined by the combination of technological opportunities, appropriability of innovations, cumulativeness of technical advances and properties of the knowledge base (specificity, complexity, tacitness and independence). Breschi et al. (2000) identified two main models of this type: the Schumpeter Mark II, or deepening model, which is characterized by high degrees of concentration of innovative activities, high stability in the ranking of innovators, and low relevance of new innovators. This model is correlated with high degrees of cumulativeness and appropriability, high importance of basic sciences and relatively low importance of applied sciences as sources of innovation. The second is the Schumpeter Mark I model, or enlargement model, characterized by low concentration of innovative activity, low stability in the ranking of innovators, and high importance of new innovators. This is correlated with low degrees of cumulativeness and appropriability, high importance of applied sciences, and an increasing role of external sources of knowledge.

Empirical studies have shown that the above patterns differ significantly across sectors, while they are mostly invariant across countries (Breschi et al. 2000; Castellacci, 2007; Castellacci and Zheng, 2010; Malerba and Orsenigo, 1996 and 1997; Montobbio, 2003; Park and Lee, 2006). They found that a Mark I model tends to prevail among traditional industries, such as furniture, agriculture and industries that rely on mechanical technology (e.g., equipment, shipbuilding, machine tools). On the other hand, a Mark II pattern is more often found in high-tech or complex sectors (including aviation, biotechnology, electronics, computers).

The Geography of Innovation

The mechanisms that foster agglomeration processes through localized externalities are mainly three: knowledge spillovers, labor pooling and factor sharing (Duranton & Puga, 2004). The debate about what spatial scale at which each mechanism takes place is recent. For technological spillovers, the literature identifies very small distances (Cainelli & Lupi, 2010). The interest of economics and innovation scholars in the geographic dimension of innovation activities of innovation has grown in recent decades (Jaffe et al. 1993; Feldman, 1994; Audretsch and Feldman, 2004; Breschi and Malerba, 2005, Feldman and Kogler, 2010). Similarly, the dynamics of knowledge production and dissemination has become a central theme of economic geography (Asheim and Gertler, 2005; Boschma, 2005; Cooke, 2001). This has generated fruitful cross-fertilization and contributed to the emergence of an interdisciplinary research area called the Geography of Innovation (Diodato & Morrison, 2019). A central tenet of this line of research is that knowledge spillovers are spatially localized. The geographic implication of this theoretical argument is that physical proximity to knowledge sources facilitates access, exploitation, and dissemination of knowledge and ultimately accelerates innovation activity at the local level (Asheim and Gertler, 2005). This cumulative process is peculiar to the way knowledge accumulates and has significant geographic consequences: it triggers a self-reinforcing clustering process that eventually leads to an uneven distribution of innovation across space (Breschi and Malerba, 2001). Another theoretical assertion in this literature is that the scope of possible innovation activities is delimited by the cognitive and technological knowledge possessed by the actors who contributed to their development (Breschi *et al.* 2003). In economic geography, a long-standing finding is that various forms of proximity are important in promoting innovation (Boschma, 2005). From a geographical perspective, the crucial implication is that regions can successfully diversify into activities that are linked to the pre-existing set of capabilities present in the region (Boschma, 2017; Rigby, 2015). In other words, path dependence strongly shapes the direction of technological change (Dosi, 1988). Despite this, the geographic distribution of innovative activities is still poorly understood (Diodato & Morrison, 2019). Von Graevenitz et al. (2021) developed a new methodology using U.S. brand descriptions of goods and services to study the spatial diffusion of innovations. They confirm a strong negative effect of distance on the diffusion of innovation. The literature intersecting the uneven distribution of innovation with technological characteristics is under-explored.

Njøs et al. (2020) point out that evolutionary economic geography has paid little attention to technological characteristics in explaining the emergence of new industries from a theoretical perspective. One exception is Diodato and Morrison (2020) who find that spatial innovation patterns change according to a technology's stage of development and differences between technologies and their dynamics over time. They also find that technological opportunities can predict changes in geographic concentration with great accuracy. Berkes and Gaetani (2021) find that the mix of ideas embedded in inventions is determined by the local technology mix. This supports the hypothesis that cross-sectoral knowledge spillovers from informal interactions are a key component of the innovation process. High-density areas promote diversification and facilitate informal interactions, leading to a higher degree of unconventionality in innovation. These findings are in line with the idea that the innovation process is a cumulative and combinatorial process. Strambach & Klement (2012) analyzed the microdynamics of knowledge at the firm level, finding that external knowledge sourcing in distributed knowledge production is a significant feature of innovative change processes. Moreover, Balland et al (2020) find strong evidence that complex knowledge is highly spatially concentrated in cities. Despite these findings there is as yet no unified framework for the micro-foundations of the agglomeration and dispersion of innovation (Crescenzi et al., 2020) and, with rare exceptions mentioned above, there are also no works that jointly analyze spatial and technological dynamics.

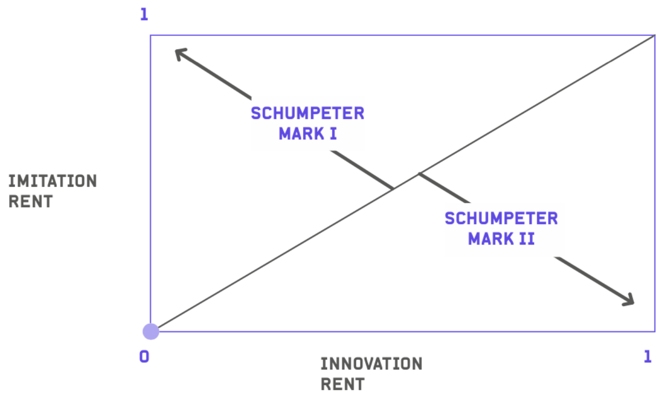
3. A framework for spatial and technological innovation

To frame the different models according to the specific characteristics of knowledge, from the previous literature review we know that the combination of technological opportunities, appropriability of innovations, cumulativeness of technical advances, and properties of the knowledge base defines a technological regime. Technological opportunities, cumulativeness of technical advances, technology specificity and high appropriability are complementary to market power. While external knowledge, low appropriability, and low specificity are complementary to market competition.

A simple two-step model was developed to analyze these characteristics together: in the first, technological characteristics are analyzed. In the second, technological characteristics and the spatial dynamics of innovation are considered together.

Starting from the results of the evolutionary economics literature, innovation rent is defined as a positive function of technological opportunities (K), cumulativeness of technical progress (T), while imitation rent is defined as a positive function of knowledge spillovers (δK) and negative function of imitation costs (I), or appropriability of innovations. The former are depicted in Fig 2 in ordinate and the latter in abscissa. And where the two different technological regimes are positioned as follows:

Fig 2: The theoretical framework for innovation in technological space



In this approach the presence of knowledge spillovers arise exclusively from the characteristics of the technological good, and not from the relation between different types of knowledge. In other words, a given market structure will have different effects on the promotion of innovation only according to the specificity technology properties, while the relationship of such technology to the local knowledge base is not considered. To add this dimension, it is necessary to consider space as well. In the next section the theoretical framework is enriched with this additional dimension.

4. Bridging technological and geographical space

It has been pointed out in the previous paragraphs that a nonrival good can be produced at zero marginal cost (or low marginal cost, depending on the degree of nonrivality) and thus can become an input to produce a potentially infinite number of goods. From a spatial point of view, the presence of localized externalities, functioning as inputs for other related technological goods, pushes toward a cumulative process of spatial concentration. If we move from the theoretical concept of nonrivality to its practical application, the possibility to be used as a factor of production depends on its fungibility, that is, its relationship with other goods. The principle of relatedness (Hidalgo et al., 2018) measures the overall affinity between a specific activity (industries, knowledge, goods, etc.) and a place. Relatedness makes it possible to identify the mechanisms that facilitate knowledge flows between industries and locations. These externalities do not spill in the air, but through specific proximity channels that depend on the relatedness between a technology and a specific place (and its knowledge base). In this way, relatedness can explain path dependencies and predict which activities will grow or decline in that location.

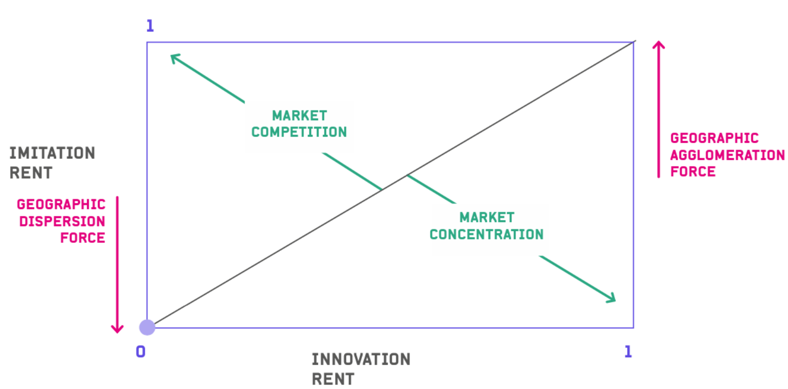
In sum, the ability of knowledge to spread across space, technologies and industries depends on its nonrivalry, but is realized through specific pathways of relatedness.

From this perspective, the opportunity to take advantage of the presence of localized technological spillovers depends on the degree of relatedness. Therefore, compared to the previous section, I denote relatedness by δRK, instead of using the generic presence of localized externalities.

To control the sign of the variables related to the properties of technological knowledge with respect to the spatial dimension, the work of Diodato and Morrison (2019) is followed, with some differences. For technological opportunities, the authors identify two different mechanisms with opposite signs: on the one hand, these would increase spatial concentration due to the quality and variety of knowledge sources; on the other hand, they would lead to lower spatial concentration because the entry of more firms results in more potential innovators, possibly distributed in different regions. Since both mechanisms are mediated by relatedness with the specific technology, this variable is considered as orthogonal to spatial concertation. As for the relationship between conditions of appropriability and spatial concentration, according to the authors this is also mediated by the presence of localized knowledge spillovers. Although they hypothesize a positive relationship, via lower technological change and higher sectoral concentration, they find a significant negative effect. Therefore, I argue that, ceteris paribus, higher imitation costs reduce the ability to capture localized externalities and thus reduce spatial concentration. Regarding cumulativeness -that is, new knowledge is highly dependent on previous cumulative knowledge- Diodato and Morrison (2019) expect all firms in that industry to benefit as they share these externalities and build their future innovation activity on them. This may result in higher geographic concentration and lower spatial entry, assuming that knowledge spillovers are highly localized. Again, the sign of the relationship seems to be mediated by the presence of localized knowledge spillovers and their appropriability. Therefore, in the framework, the relationship between cumulativeness and spatial concentration is orthogonal.

Once all relationships are considered, the theoretical framework is enriched with the spatial dimension as follows:

Fig 3: The theoretical framework for innovation in technological and geographic space



Using the developed framework, it is possible to analyze which characteristics of knowledge favor concentration processes and which favor dispersion processes. This framework gives rise to four different results in terms of geographic and market concentration, based on the interaction between the different degree of rent from innovation and imitation, and incorporating different combinations of relatedness between the technological good and a specific location.

Fig 4: The 4 different patterns of innovation in technological and geographic space

		INNOVATION RENT	
		LOW	HIGH
IMITATION RENT	LOW	GEOGRAPHIC DISPERSION AND CO-EXISTENCE OF MP AND MC	GEOGRAPHIC DISPERSION AND MARKET POWER
	HIGH	GEOGRAPHIC CONCENTRATION AND MARKET COMPETITION	GEOGRAPHIC CONCENTRATION AND CO-EXISTENCE OF MP AND MC

If the four patterns are numbered clockwise starting from the upper left quadrant, the first one involves geographic dispersion and an intermediate level of market concentration. This would seem to represent innovation embedded in unsophisticated goods (low technological opportunity and low ability to capture localized externalities resulting from a low knowledge base) that fails to create cumulativeness and thus market concentration, but neither does market competition given high imitation costs. The second pattern represents Schumpeter's traditional Mark II, with a high degree of market power and geographic dispersion. The third can be interpreted as based on complex innovation that, on the one hand, produces high technological opportunities and, on the other, a high ability to capture localized externalities by virtue of high absorptive capacity leading to geographic concentration and an intermediate level of market power (consistent with Ballad et *al*., 2020 results). This is because, on a side, cumulativeness pushes toward concentration, on the other side, low appropriability and high technological opportunities push toward greater competition. Finally, pattern 4 represents the Schumpeter Mark II characterized by market competition and geographic concentration.

5. Conclusions

This paper revisits different strands of literature straddling innovation economics and economic geography to re-read the innovation puzzle through the lens of the spatial dimension. Contributions from evolutionary economics have provided several tools for unpacking the relationship between innovation and market structure. Based on these, the possible relationships between each of them and spatial dynamics were traced. From a theoretical point of view, the non-fungibility of knowledge makes it possible to consider the specificity of knowledge no longer as an absolute but as a relative property. The relationship between localized externalities and innovation is mediated by the degree of relatedness between the two, and this constrains the flow of knowledge. Relatedness, which measures the affinity between knowledge and a place, is embedded in the evolutionary technological framework. This perspective can help provide new insights to the innovation puzzle by helping to distinguish different innovation patterns based on knowledge characteristics, specific local knowledge bases and relative market structure (market competition or concentration). The framework identifies 4 different patterns: i. Geographic Concentration and Market competition: with low innovation rent and high imitation rent; ii. Geographic Dispersion and Market power: with innovation rent high and imitation rent low; iii. Geographic Concentration and co-existence of Market competition and Market power: with innovation rent and imitation rent high; iv. Geographic Dispersion and co-existence of Market Competition and Market Power: with innovation rent and imitation rent low.

This framework can be easily enriched by using other methodologies that can capture the relationship between different technological intangibles. Indeed, A growing literature analyzes the technological distance between intangibles, which basically measures their complementarity in production (Yan & Luo, 2017) or their specifity and complementarity (Petralia, 2020). Finally, this framework will need to be verified empirically. To do this, the use of patents, while the most developed and widely used indicator for assessing innovativeness, has several limitations (Castaldi, 2020). The most important of which in relation to the focus of this paper is that it selects only a type of knowledge that by its nature has a high degree of appropriability.

From a policy perspective, the development of understanding at the intersection of technological and space dynamics can help move industrial policies toward a more place-based approach and smart specialization strategy toward greater integration of institutional aspects related to market structure and intellectual property rights regulation.

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3.

Unpack local complexity

The role of external capabilities and regional linkages in Italian local labor systems

The use of traditional data (exports, patents and employment) in complexity methods makes it difficult to disentangle the contribution of external and local capabilities to economic performance. Furthermore, these methodologies do not help to evaluate the role of intra- and inter-regional linkages. In this work, imported and exported value added are used as measures of external and local productive capabilities, respectively. By applying the methodologies of Economic Complexity, backward (input-related) and forward (output-related) complexity are defined and used to study their contribution to productivity and GDP level of Italian local labor systems. In addition, using the Leontief's procedure, value added activated by final demand localized at different geographic scales is decomposed to measure the contribution of multilevel regional linkages and Global Value Chain participation. The results show that: i. forward complexity has a similar ability to explain variance in GDP per capita and productivity levels as the employment complexity; ii. Intra-regional, inter-regional and international capabilities appear to contribute to GDP per capita and productivity levels in ways specific to the degree of development; iii. both forward and backward complexity contribute to productivity growth, and more markedly to the growth of knowledge-intensive sectors, for SLLs with sufficient absorptive capacity. From a policy perspective, it follows that anchoring and positioning on multiscalar networks must be aligned with local absorptive capacities and degree of development.

Keywords: Regional Economics; Economic Complexity; Evolutionary Economic Geography, GPN; GVCs; Input-Output; Local labor Systems.

1. Introduction

This paper stands at the intersection of Evolutionary Economic Geography (EEG) and the literatures on global value chains (and GPNs) to analyze Italy's Local Labor Systems (SLLs) in terms of local capabilities, external capabilities and participation in networks at different spatial scales. The EEG literature emphasizes that the ability to develop new activities and upgrade existing ones depends on the presence of regional capabilities (Cooke, 2005). The local capabilities approach is strongly related to the Resource Based View (RBV) of firms (Wernerfelt, 1984; Barney, 1991). Both understand their objects of study as bundles of resources. Resources confer sustained competitive advantage if they are valuable, rare, and difficult to imitate and substitute (Barney, 1991). As Neffke et al. (2018) point out, and in continuity with the GVCs approach, firms also use locally available external resources. The literature on GPNs and GVCs is particularly extensive and highlights the benefits to firms and places of participating in global networks. Moreover, these benefits can occur through both forward and backward participation. While the different mechanisms of learning from the multiplicity of organized networks at different spatial scales are poorly explored in the literature. The study of the interaction between local and external capabilities is rather recent (Balland and Boschma, 2021; Colozza et al. 2021). The present work fits into this nascent literature by applying a new methodology to disentangle the contribution of different production geographies that pivot on local labor systems. Specifically, Economic Complexity analysis and I/O tools are used to study the contribution to the economic performance of SLLs resulting from positioning in intra-regional, inter-regional and global networks (GPNs or GVCs). In addition, these methodologies allow the contribution of local and external capabilities to be separated.

The development and refinement of economic complexity methodologies have provided new tools for the study of local capabilities (Hidalgo & Hausmann, 2009). These studies have covered the national level, the subnational level and, in some cases, the urban level. In contrast, there are no applications of Economic Complexity methodologies to LLSs. Moreover, these methodologies, being applied mainly to exports, patents, and employment, are unable to distinguish the presence and rarity of locally available external resources. To address these two gaps, complexity methodologies will be applied to the imported and exported value added of Italian SLLs to distinguish the contribution of local (Forward Complexity) and external (Backward Complexity) productive capabilities. SLLs enclose municipalities with a high degree of self-containment of commuting workers. This high level of geographic disaggregation appears particularly fruitful for the analysis of local capabilities because it encloses the effects of two dimensions of agglomeration forces: labor pooling and knowledge spillovers. Indeed, knowledge spillovers operate overwhelmingly at very small spatial scales (Rosenthal and Strange, 2020). While thanks to the presence of I/O data it is possible to disentangle the third dimension of the agglomeration economies, that is, external networks and to separate the effect of networks operating at different spatial scales.

In this way, this paper aims to fill two areas under-studied in the literature: how participation in networks operating at different spatial scales (global, interregional, and intraregional) contributes to the economic performance of LLSs. In addition, this work is the first to apply Economic Complexity methodologies to the value added activated by the participation of SLLs in Global Value Chains.
The results of this work make several innovative contributions: i. They show that complexity indicators are strongly correlated with productivity and GDP per capita levels even at a highly disaggregated spatial level; ii. They find that the complexity indicator calculated on the value added activated by international networks performs similarly to the employment complexity indicator despite being calculated on an extremely smaller number of sectors. iii. They allow; thanks to the possibility of decomposing value added, to show that intra-regional, inter-regional and international capabilities appear to contribute to GDP per capita and productivity levels in ways specific to the degree of development; iv. They show that Forward Complexity and Backward Complexity contribute to productivity growth and more markedly to growth in knowledge-intensive sectors.
These results indicate that knowledge embedded in intraregional and interregional linkages contributes positively to the economic performance of less developed local systems, while knowledge embedded in interregional and international networks contributes positively in more developed ones. This seems to suggest that path dependency concerns place but also relational characteristics in terms of the spatial scale of knowledge embedded in productive networks. Finally, these results confirm the need to develop sufficient absorptive capacity to reap the benefits of participation in international networks. Moreover, from a policy perspective, they suggest anchoring and positioning on networks at different spatial scales depending on the level of development.

2. Literature review

Local economic complexity

The development of complexity methods has given new impetus to the study of regional capabilities. In fact, Economic Complexity (EC) provides methods that through the analysis of goods that are located in the territory infer the presence of local productive capabilities. Economic complexity offers a potentially powerful paradigm to understand key societal issues and challenges of our time (Balland *et al.*, 2022). In recent years a large literature has developed that applies the tools of EC to the study of regional systems, and only recently also to cities (Balland & Rigby, 2017; Gao & Zhou, 2018; Balland et al., 2020). The study of economic complexity accelerated during the last decade thanks to two contributions. The first involved the introduction of metrics of relatedness (Hidalgo et al., 2007), which measure the overall affinity between a specific activity and a location, explain path dependencies and predict which activities will grow or decline in a location. The second contribution was the development of metrics of Complexity and Fitness (Hidalgo & Hausmann, 2009; Tacchella et al., 2012). These use data on the geography of activities (such as exports by country or region, or employment by city and industry) to estimate the availability, diversity and sophistication. In this approach, an economy is seen as a system of knowledge accumulation, and its prosperity depends upon whether it can make ever more information grow (Hidalgo, 2015). Given the effectiveness of complexity measures at the national level, a natural extension is to apply them to subnational and metropolitan regions, which are the fundamental unit of economic geography (Jacobs, 1969; Storper, 1997) and the hub of global economy. Attempts have been made to apply these metrics in China, Australia, and the United States (Gao & Zhou, 2018; Reynolds et al., 2018; Sbardella et al., 2017). Balland & Rigby (2017) Found that knowledge complexity is unevenly distributed among U.S. cities and is not reflected in a corresponding level of patents. Balland et al. (2020) found that the urban concentration of complex economic activities has been continuously increasing since 1850. These findings suggest that the increasing urban concentration of jobs and innovation might be a consequence of the growing complexity of the economy. In a similar way, Benedict et al. (2019) found that the highest complexity areas are major cities, while traded industries tend to rate higher on complexity than local serving ones. Dong (2022) investigates the relationship between industrial land policies and complex diversification. Cicerone et al. (2017), combining a measure of the centrality of a province's exports within the export network with the absolute values of the revealed comparative advantage, show that better positioned provinces in Italy boast stronger regional development. In addition, a literature is developing that through various methodologies analyzes complexity at the local level through data on employment (Davies & Marè, 2021; Gomez-Lievano & Patterson-Lomba, 2019; Fritz & Manduca, 2022; Mealy & Coyle, 2021). To the best of our knowledge, there is no work that applies complexity methodologies to a unit as disaggregated as the local labor system. This is unfortunate because these are functional units of analysis that enclose the highest degree of self-containment of commuting workers and are not predetermined ex-ante by administrative boundaries. Thus, they represent a "functional" economic unit that changes over time and can provide more accurate information on local capabilities.

Local and external capabilities

Firm-external resources have been identified in a variety of literatures. For instance, Strambach & Klement (2012) investigated micro-dynamics of knowledge at the firm level, finding that sourcing of external knowledge in distributed knowledge production is a significant feature of innovative change processes. The fact that the capacity to absorb external information is largely a function of the firm's level of prior knowledge is well known in the literature (Cohen & Levithal, 1990). In the literature on innovation the production of new knowledge at firm level depends on both complementary factors: internal skills and external sources of knowledge (Antonelli, 2007). More generally economic geographers argue that firms benefit from agglomeration externalities that derive from intra-regional labor market pooling, input-output linkages and knowledge spillovers (Glaeser *et al.*, 1992; Henderson *et al.*, 1995; Almeida and Kogut, 1999; McCann and Simonen, 2005; Faggian and McCann, 2006). But in both cases, with rare exceptions (Balland and Boschma, 2021; Colozza et al., 2021), there are no studies that analyze the relationship between local and external capabilities through the methods of complexity. The study of the interaction between local and external capabilities is quite recent. From this perspective, it is well established that interregional linkages are considered to give regions access to external knowledge and avoid lock-in (Ascani et al., 2020; Boschma and Iammarino, 2009; Giuliani and Bell, 2005). Balland and Boschma (2021) found evidence that external linkages strengthen local capabilities when they provide access to knowledge that is absent in the territory (complementary capabilities). Colozza et al. (2021) found that regions with high economic complexity benefit more from both regional capabilities (as proxied by a high relatedness between local activities) and external linkages in terms of GVC participation. Participation in GVCs also includes locally produced goods and thus also incorporates a relevant part of local capabilities. And because of this, it does not allow proper disentanglement between local and external capabilities. In fact, in the literature, backward participation is the supply of foreign inputs for a country's export production, while forward participation is the supply of inputs to foreign partners for their export production (Baldwin, 2006). From an economic function point of view, backward participation allows a country to use inputs containing high-quality technology and thus can be used as an indicator of external capabilities that an economy makes use of; while forward participation represents the local capabilities present in a place that contribute to the production of goods embedded in global chains. Technological spillover can be expected from both backward participation (Urata & Baek, 2019), through knowledge acquisition, and forward participation, through information about technology and management know-how from the export destination. There is evidence in the literature that both forward and backward participation increase countries' productivity (Kummritz, 2016; Constantinescu et al., 2019).

Moreover, to the best of our knowledge there is no work investigating the relationship between local and external capabilities at a smaller spatial scale. In fact, a second gap in the literature is what is meant by external capabilities and what is meant by internal capabilities. Of course, this depends on the unit of analysis we adopt. In general, it is true that the more disaggregated the unit of analysis the greater the possibility of properly identifying pools of homogeneous local capabilities. In addition, we know from well-established literatures that there are three mechanisms that favor agglomeration processes through localized externalities: knowledge spillover, labor pooling and input sharing (Duranton & Puga, 2004). The debate between which is the spatial scale at which each mechanism take place is recent. For labor pooling and input sharing, the local labor system scale and the regional scale seem to operate, respectively. For technological spillovers, the literature identifies very small distances (Cainelli and Lupi, 2010; Rosenthal and Strange, 2020; Bartelme and Ziv, 2021; Lavoratori and Castellani, 2021). From this perspective, local labor systems seem to be ideal places to analyze the interaction between local and external capabilities.

Source of external capabilities from EEG perspective

The first systematic work that traces the points of connection between Global Value Chain (GVC) and EEG literatures is Boschma (2022). In which all research strands of economic geography that share an interest in GVCs are traced: the GPN literature (Coe et al., 2008, 2004; Ernst & Kim, 2002; Henderson et al., 2002); the literature focusing on the relationship between clusters and GVCs (Giuliani et al., 2005; Humphrey & Schmitz, 2002; Morrison et al., 2008; Pietrobelli & Rabellotti, 2011); the global innovation systems/networks (GIS/GIN) literature (Binz et al., 2016; Chaminade et al., 2016; Cooke, 2013; Ernst, 2009); and the literature on the 'geography of functions' (Los et al., 2017; Timmer et al., 2019). Regarding the former, as Yeung (2021a) noted, evolutionary economic geography (EEG) and global production networks (GPNs) have developed in parallel. Yeung argued that EEG emphasizes the role of intra-regional capabilities rather than interregional linkages. Although recent papers on regional diversification in EEG have begun to empirically address the role of non-local linkages (e.g., Balland & Boschma, 2021; Miguelez & Moreno, 2018), how relatedness might enhance the regional spillovers of multinational firms (e.g., Ascani & Gagliardi, 2020; Cortinovis et al., 2020), and whether related or unrelated diversification is promoted by multinational firms (Elekes et al., 2019; Neffke et al., 2018). Yeung (2021a) connected the GPN concept of strategic coupling to the EEG concept of related and unrelated diversification proposed by Boschma et al. (2017).

Regarding the GPN-EEG nexus, Boschma (2022) identifies some limitations and open issues related to the subject of this paper. For the former GPN focuses almost exclusively on individual GPNs and less on relationships with other GPNs. For the latter what types of network linkages (in terms of proximities) are needed to overcome regional lock-in (Rodríguez-Pose, 2021)? What part is played by interregional linkages that give regions access to new capabilities that are complementary to their own capabilities?

As for the literature on clusters and GVCs, this builds on the seminal work of Becattini (1979) and Porter (1998) on the importance of clusters and industrial districts for regional development. Clusters would reduce transaction costs, enable collective action, strengthen local networking, and induce local knowledge spillovers. Insights from evolutionary economics were adopted to emphasize the importance of cumulative, collective, and localized learning in clusters (Maskell & Malmberg, 1999), embodied in concepts such as innovative milieux (Camagni, 1991), regional innovation systems (Cooke, 1992), technological districts (Antonelli, 1994; Storper, 1992), and learning regions (Asheim, 1996; Morgan, 1997). The main focus was on local assets and the localized learning that clusters provide to firms. However, less attention was paid to external linkages, although cluster firms are often active in VCs (Giuliani et al., 2005). In the early 2000s, a large literature on GVCs picked up on this theme and focused on the role of global linkages in fostering upgrading in clusters (Guerrieri et al., 2001; De Marchi et al., 2018a, 2018b; Pietrobelli & Rabellotti, 2007; Turkina & Van Assche, 2018). In many of these studies, the focus has been on identifying opportunities for local producers to learn from a VC's global leaders (Gereffi, 1999). Humphrey and Schmitz (2002) were the first to recognize the importance of linking clusters (with a focus on local linkages within the cluster) to GVCs (with a focus on cross-border linkages). Over the past two decades, a rich literature has explored the link between clusters and GVCs. According to Boschma (2022) what needs to be further explored is the interaction between local capabilities and GVCs (Kano et al., 2020), the extent to which GVCs contribute to the development of new pathways in clusters, and how this depends on the complementarity between local and nonlocal capabilities (Balland & Boschma, 2021).

The literature on GINs (Chaminade et al., 2016; Cooke, 2013; Ernst, 2009; Wagner & Leydesdorff, 2005) shares a similar focus on learning and innovation in global networks with the previous literature. The focus is explicitly on actors organized in networks that are collectively engaged in knowledge production. These scholars have applied evolutionary concepts to the study of GIS/GINs, such as capacity and learning, network proximity, innovation systems, and complex systems. The contributions of this literature concern the quantitative study of the dynamics of relocation of global networks of business ties, research collaborations (De Rassenfosse & Seliger, 2020), co-publications (Fitzgerald et al., 2021), co-inventions, and patent citations (Montobbio & Sterzi, 2011). Another emerging literature regarding multiscalar networks in GIS focuses on the path creation processes beyond a territorial system perspective (Binz & Truffer, 2017; Binz et al., 2014). This literature investigates how firms and other actors mobilize and anchor resources for the formation of new industries from outside the region (Binz et al., 2016). However, according to Boschma (2022) there is still little understanding of the effect of global knowledge networks on regional development (Parrilli et al., 2013) and the ability of regions to diversify and enhance their GVCs.

A key question in the GVC literature is which countries/regions are able to develop or participate in new GVCs or improve existing ones. The recent literature termed "geography of functions" was developed by scholars at the University of Groningen using new World Input-Output data (Los et al, 2015; Timmer et al., 2015). This pioneering literature argues that countries and regions specialize in tasks or functions in GVCs rather than in particular products or industries, resulting in a fragmented structure of activities across space (Timmer et al., 2019). Functions differ not only in terms of their dependence on specific inputs, but also in their propensity to be spatially sticky (Timmer & Pahl, 2021). Despite some exceptions GVCs have not been a key unit of analysis in EEG research to date. While EEG has generated new knowledge on related diversification across regions (Hidalgo et al., 2007, 2018; Neffke et al., 2011), little knowledge still exists on how GVCs contribute to regional diversification and how GVCs evolve through path-related diversification in terms of upgrading and downgrading (Boschma, 2022). To explain the dynamics of GVCs in regions from a relatedness framework, a new unit of analysis is needed, namely the region-industry function, which considers potential combinations of horizontal and vertical upgrading (Ye, 2021). While horizontal upgrading has so far been a key topic in the EEG literature on regional diversification, vertical upgrading has been in the GVC literature. A next logical step is to combine horizontal and vertical upgrading by focusing on new industrial functions and their externalities (Boschma, 2022). Finally, although global Input-Output data are increasingly regionalized, another challenge is the availability of more disaggregated data with more industrial categories (Los et al., 2017; Timmer et al., 2019).

From an evolutionary perspective, these different literatures emphasize the different mechanisms occurring at different spatial scales that can promote anchoring and accumulation of external resources and avoid lock-in. The following sections will present an empirical strategy that aims to provide some answers to the open issues that cut across these literatures. Through the decomposition of networks operating at different spatial scales, it will be possible to assess how intra- and interregional linkages or participation in global value chains contribute to the economic performance of Italian local labor systems. In addition, the indicators developed allow us to isolate the effects of participation in forward and backward GVCs as a proxy for local and external capabilities. Finally, the specific indicator we constructed, which measures the multiplicity and sophistication of knowledge embedded in local firms participating in global value chains, allows for a measure that accounts for vertical (sophistication) and horizontal upgrading (diversification).

3. Methodology and data

3.1 Dataset

These areas should somehow be representative of the local labor market, or in other words, be "functional" rather than administrative areas, such as local labor systems (LLS) or travel-to-work areas (TTWA) (ISTAT 1997; Coombes et al. 2012). The LLSs were defined by the Italian National Statistical Institute (ISTAT) for the first time in 1981 in collaboration with Istituto Regionale per la Programmazione Economica della Toscana (IRPET) and the University of Newcastle in the UK. Since they are functional areas and depend on commuting flows, they are dynamic in nature, and their definition has been revised since their creation in conjunction with the release of the decennial Censuses (1991, 2001 and 2011). Not surprisingly, as commuting flows lengthened over time, the number of LLS has decreased from an initial number of 955 in 1981 down to 616 in 2011.

IRPET provides a 2016 Local Labour System level multiregional Supply and Use Table, in which Italy is disaggregated into 589 SLLs and production into 31 sectors. In addition Foreign flows are aggregated into a single sector. The table construction methodology can be found in Paniccià and Rosignoli (2018)**.** The difference between 616 and 589 local systems of labor depends on the fact that the local systems of the Basilicata, Molise and Valle d'Aosta regions were aggregated in the IO tables into three unique SLLs corresponding to each region. Table 1 provides some descriptive statistics of IO tables.

In addition, Frame SBS (ISTAT, 2016; ISTAT, 2019) were used to calculate employment complexity, which covers several economic indicators for the population of Italian firms aggregated at the local labor system level. Specifically, information is provided for more than 4 million firms regarding employees, value added, economic sector, and other characteristics such as internationalization, membership in business groups, and foreign capital participation. As for 2016 there are 799 sectors, while for the year 2019 there are 802 sectors.

The OECD taxonomy of economic activities based on R&D intensity (2016) was used to identify the sectors with high knowledge intensity. Specifically, the knowledge-intensive high (HIT) and medium-high (MHT) manufacturing sectors and the knowledge-intensive technology (HITS) and market services (KWNMS) sector were considered.

As for the variable industrial districts, it was constructed as a dummy variable equal to 1 if the local system is considered an industrial district in the 2011 census elaborated by ISTAT (with a total of 141 districts). The metropolit variable concerns membership in one of Italy's 14 metropolitan cities.

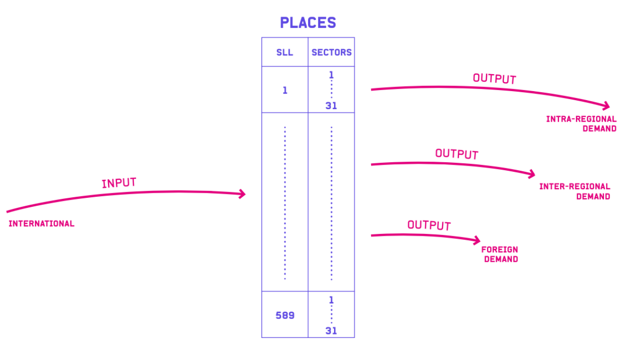
Table 1: summary statistics of IO tables

Year	N.	Sectors	Av. PIL	Min	Max	SD
2016	589	31	2517.171	660.53	23596.19	2539.051

3.2 GVSs and regional complexity indicator

Economic complexity and fitness indicators are based on a methodology that calculates product or industry complexity based on the ubiquity of each product/sector. The underlying assumption is that the less ubiquitous a product is, the more complex it is. The complexity of a place is a positive function of the diversity and sophistication of the goods produced. And this is a measure of the sectoral or product capacities present in a place. But there are not only sectoral capabilities, but also geographic capabilities, understood as the ability to enter new markets. In fact, tradable goods abroad properly reflect comparative advantages, while non-tradable goods may reflect another set of underlying capabilities (Fritz & Manduca, 2021). Exports at different spatial scales may also have different economic significance. And input-output tables make it possible to decompose the value added produced and imported at different geographic scales to analyze related characteristics.

Fig 1: sectoral and geographical capabilities



Specifically, I calculated the value added of input-output flows activated by interregional and intra-regional final demand (fd). In addition, the use of IO tables at the local labor system level makes it possible to decompose the value added activated by foreign demand. This makes it possible to assess the impact of resources positioned at different spatial scales and with respect to function (forward or backward). Through Leontief's procedure I calculate 2 matrices VX_{cs} and VI_{cs} representing exported (forward) and imported (backward) value added activated by foreign demand, respectively:

$$VX_{cs} = X(I-A)^{-1} * fd\_foreign$$
$$VI_{cs} = (X(I-A)^{-1} * fd\_foreign)^{T}$$

And I calculated other 2 matrices representing the value added exported $VX^{\boldsymbol{inter}}$ and $VX^{\boldsymbol{intra}}$ according to the spatial scale of intra- or inter-regional activation:

$$VX^{\boldsymbol{inter}} = X(I-A)^{-1} * fd\_interegional$$
$$VX^{\boldsymbol{intra}} = X(I-A)^{-1} * fd\_intraregional$$

Following Koch (2021) I used a weighted adjacency matrix of value-added activated from foreign demand. This is equivalent to considering the added value that is produced through the participation of local labor systems in global value chains. I calculated the share of value-added for both exports and imports W_{CS}^{X} and W_{CS}^{I} as proxies of local and external capabilities. Their elements are defined as the share of value-added export/import (VX/VI) a LLS (Local Labour System) c has in industry *s*. In the same way I calculated the share of value-added exports activated from intra and inter-regional demand:

i. Share of **value-added exports** activated from foreign demand:

$$(1) \qquad W_{CS}^{X} = VX_{cs} / \sum_{c} VX_{CS}$$

ii. Share of **value-added imports** activated from foreign demand:

$$(2) \qquad W_{CS}^{I} = VI_{cs} / \sum_{c} VI_{CS}$$

i. Share of **value-added exports** activated from intra-regional demand:

$$(3) \quad W_{CS}^{intra} = VX_{cs}^{intra}{}_{cs} / \sum_{c} VX_{cs}^{intra}$$

ii. Share of **value-added exports** activated from inter-regional foreign demand:

$$(4) \quad W_{CS}^{inter} = VX_{cs}^{inter}{}_{cs} / \sum_{c} VX_{cs}^{inter}$$

These adjacency matrices allow for calculating Economic Fitness in terms of value-added exports and imports at different spatial scales. I started with the share of **value-added exports** activated **from foreign demand** W_{CS}^{X}, in the following referred to as $ForwardComplexity$. Analogous to Tacchella et al. (2012, 2013), it is defined as an iterative process of order N such that:

$$ForwardComplexity_{c,N} = \frac{\tilde{F}_{c,N}}{\frac{1}{C}\sum_{c} \tilde{F}_{c,N}}$$

$$Q_{s,N} = \frac{\tilde{Q}_{s,N}}{\frac{1}{S}\sum_s \tilde{Q}_{s,N}}$$

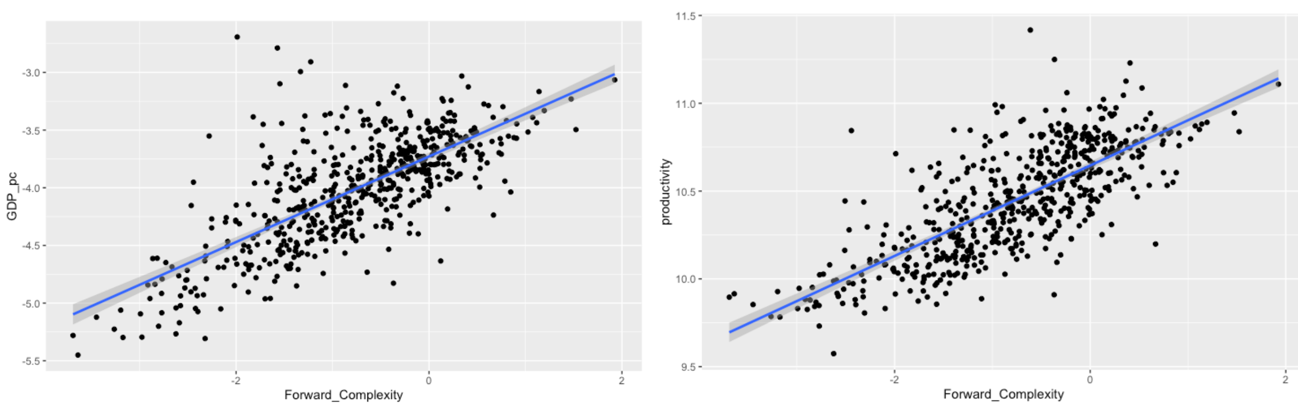
Where $\tilde{F}_{c,N}$ and $\tilde{Q}_{s,N}$ are defined as:

$$\tilde{F}_{c,N} = \sum_s W_{CS}^X \, Q_{s,N-1}$$

$$\tilde{Q}_{s,N} = \frac{1}{\sum_c W_{CS}^X \, (\, 1/VXF_{c,N-1})}$$

The starting values are set to $\tilde{Q}_{s,0} = 1$ ∀s and $\tilde{F}_{s,0} = 1$ ∀c. $\tilde{F}_{c,N}$ describes the weighted sum of industry complexity levels $\tilde{Q}_{s,N}$, weighted by the share of value-added exports country c has in the respective industry. After normalizing $\tilde{F}_{c,N}$ at every iteration, $ForwardComplexity_{c,N}$ denotes the complexity level associated with country *c*. The auxiliary variable $\tilde{Q}_{s,N}$ shows that an industry's complexity is positively related to the complexity of countries exporting significant value-added in that industry. Due to the normalization at every step, $ForwardComplexity_{c,N}$ and $\tilde{Q}_{s,N}$ converge to a unique value for every *c* or *s*, respectively.

Fig. 2a and 2b: Forward complexity and GDP per capita (on the left) and productivity (on the right)



By repeating the process for the other matrices (W_{CS}^I, W_{CS}^{intra}, W_{CS}^{inter}) we obtain the Economic Fitness measures related to forward or backward positioning and different spatial scales: forward complexity, backward complexity, inter-regional complexity and intra-regional complexity. Table 2 describes the different indicators of economic complexity according to the spatial scale of the network and the resources activated. While table 3 local labor systems sorted by the 4 indicators of complexity[1].

[1] In the supplementary material a more extensive version is available.

Table 2: description of different spatial indicators of economic complexity

Matrix	Name	Description	Resources	Network
W_{CS}^{X}	**Forward Complexity**	Quantifies the diversity and sophistication of exported value added activated by direct and indirect foreign demand.	Local capabilities	Forward participation in GVCs (or GPNs)
W_{CS}^{I}	**Backward Complexity**	Quantifies the diversity and sophistication of value added imported from abroad and used for local production.	External capabilites	Backward participation in GVCs (or GPNs)
W_{CS}^{intra}	**Inter-regional Complexity**	Quantifies the diversity and sophistication of value added exported to other Italian regions.	Interregional capabablities	Interregional linkages
W_{CS}^{inter}	**Intra-regional Complexity**	Quantifies the diversity and sophistication of value added exported within its region.	Intraregional capabablities	Intraregional linkeges

Table 3: Local labor systems sorted by the 4 indicators of complexity

	Forward_Complexity	Backward_Complexity	Interregional_Complexity	Intraregional_Complexity
1	MILANO	MILANO	MILANO	MILANO
2	TORINO	TORINO	ROMA	ROMA
3	ROMA	BOLOGNA	BASILICATA	VENEZIA
4	BOLOGNA	ROMA	TORINO	TORINO
5	FIRENZE	BERGAMO	BOLOGNA	BOLOGNA
6	BERGAMO	VENEZIA	NAPOLI	BERGAMO
7	GENOVA	BUSTO ARSIZIO	FIRENZE	MOLFETTA
8	VENEZIA	FIRENZE	BERGAMO	CORREGGIO
9	PADOVA	CAGLIARI	VENEZIA	NAPOLI
10	BUSTO ARSIZIO	UDINE	PADOVA	BARI

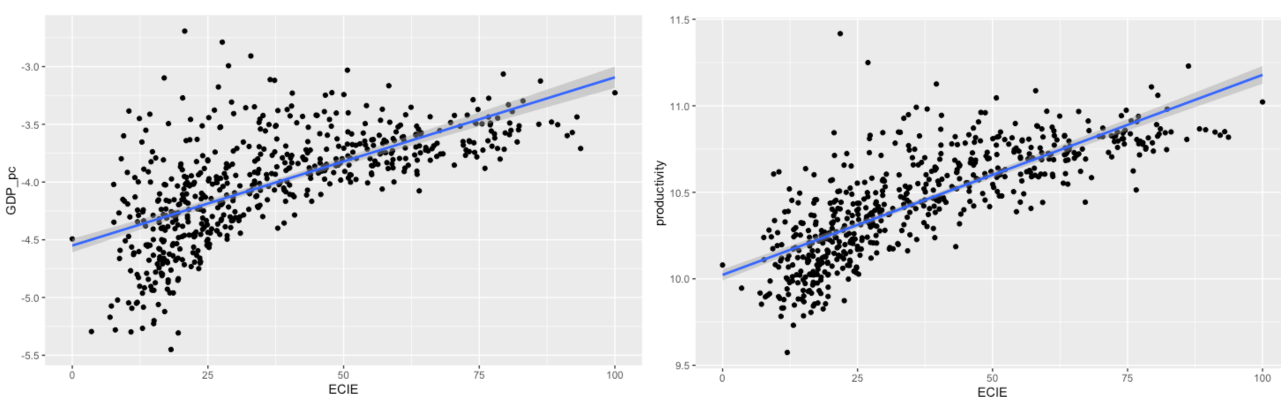
3.3 Economic Complexity on Employment

To test the robustness of the new complexity indicators proposed earlier we compare them with the more traditional Economic complexity indicator based on the Method of Reflections (Hidalgo & Hausmann, 2009). The construction of the latter follows the procedure of Mealy and Coyle (2022) and is applied to local employment in the 589 local labor systems relative to 799 industries. To calculate The Economic Complexity Index on Employment (ECIE), a binary matrix M is constructed based on the local location quotients in the different Industries. An industry *j*'s location quotient in a given area *i* is calculated as the ratio of the industry's share of employment in that location to its share of employment nationally. Defining E_{ij} as the number of people in local labor System i employed in industry j, the location quotient for industry j in area i is given by:

$$LQ_{ij} = \frac{E_{ij}/\sum_j E_{ij}}{\sum_i E_{ij}/\sum_i \sum_j E_{ij}}$$

Following Mealy and Coyle (2022) a location quotient greater than 1 (which indicates that the SLL's employment share in that industry is greater than the national average) conveys that the SLL has some degree of competitive strength in that industry. Variations of this procedure have been proposed by Davies and Marè (2019) and Gomez-Lievano and Patterson-Lomba (2019) in which the matrix is constructed according to different specifications to improve the identification of competitive advantages. Fritz & Manduca (2022) for example include additional criteria such as a minimum number of employees of 50 to avoid problems of sublinear scaling and undercounting. In any case, the correlation between these different specifications is very high (0.966-0.990) and does not seem to make a difference for the purposes of the analysis. Through the EconGeo package (Balland, 2019) we calculate the ECIE and obtain the following plots (fig. 3a and 3b)

Fig 3a and 3b: ECIE and GDP per capita (on the left) and productivity (on the right)



3.4 Empirical validation

First, we want to evaluate the complexity indicator constructed through the value added activated by participation in global production networks. This methodology is equivalent to that developed by Koch (2020) with two differences: i. in this case the unit of analysis is the local labor system and not the country; ii. here we consider not only value added exported abroad but also value added exported to another local labor system but activated by foreign demand.

Figure 3 shows plots of forward complexity and GDP per capita (on the left) and productivity (on the right). In the supplementary material, Figure 4 provides information on macro-region membership, in which it can be seen that the indicator manages to separate SLLs belonging to northern, central and southern regions.

This new indicator is compared with the traditional Employment Complexity indicator (ECIE) and the Openness indicator (VAX) used in the international economics literature (Johnson & Noguera, 2011). Table 4 shows the results of pairwise correlation with the two traditional economic performance indicators (GDP per capita and productivity). For GDP per capita the Forward Complexity indicator is more correlated than the others (0.719 vs. 0.6781 and 0.6663). While for productivity Forward Complexity is slightly less correlated, although in all cases extremely high, as the differences narrow (0.7564 vs. 0.7910 and 0.7745).

Table 4: Pairwise correlation of indicators in relation to GDP per capita and productivity

PWCORR	GDPpc*	Productivity*
forwardcomplexity	0.7191	0.7564
ECIE	0.6781	0.7910
VAX	0.6663	0.7745

Tables 5a shows the ability of the 3 indicators to explain the variance of productivity and GDP per capita. Forward complexity R-squared is 0.517 (vs 0.46 and 0.444) for GDP per capita and 0.572 for productivity (vs 0.626 and 0.600). In the supplementary material (table 5b) we repeat the analysis by removing the 88 smallest SLLs (<15,000 population). The results improve and the R-squared of forward complexity becomes 0.597 and 0.594, respectively.

Tables 5a: OLS regression on different indicators to explain variance in productivity and GDP per capita.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES*	**GDPpc**	**GDPpc**	**GDPpc**	**Productivity**	**Productivity**	**Productivity**
VAX	0.428***			0.324***		
	(0.0198)			(0.0109)		
ECIE		0.539***			0.409***	
		(0.0241)			(0.0131)	
forwardcomplexity			0.376***			0.257***
			(0.0150)			(0.00919)
Constant	3.158***	5.871***	3.728***	11.10***	9.042***	10.65***
	(0.0425)	(0.0841)	(0.0180)	(0.0234)	(0.0455)	(0.0110)
Observations	589	588	589	589	588	589
R-squared	0.444	0.460	0.517	0.600	0.626	0.572

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

* In logarithmic form.

These results show that the indicator has a comparable ability to explain variance to that of Employment Complexity despite having an extremely smaller number of sectors (31 vs. 799). Also, as we will see in the next sections this new methodology makes it possible to disentangle between exported and imported value added and to analyze networks operating at different spatial scales.

3.5 Empirical Model

In the baseline model, referring to the year 2016, GDP per capita and productivity are explained by Forward Complexity and a set of control variables:

$$(1) \quad ln(Y_i) = \alpha_i + \beta_1 \ln\,(Forward\_Complexity_i) \; + \boldsymbol{X_i}\,\theta + \alpha_r$$

Where Y_i represents the performance of SLL i inter of both GDP per capita and productivity; $\boldsymbol{X_i}\theta$ represents the vector of control variables (membership in industrial districts and metropolitan cities, population, and presence of business networks); α_r is the fixed effects at the regional level.

To assess the role of external and local capabilities, Forward Complexity and Backward Complexity were added in the regression:

$$(2) \quad ln(Y_i) = \alpha_i + \beta_1 \ln\,(Forward\_Complexity_i) + \beta_2 \ln\,(backward\_Complexity_i) + \beta_3 \ln\,(backward\_Complexity_i * Forward\_Complexity_i) \; + \boldsymbol{X_i}\,\theta + \alpha_r$$

Finally, complexity is unpacked by spatial scale, and the complexity of intra-regional and inter-regional linkages are added:

$$(3) \quad ln(Y_i) = \alpha_i + \beta_1 \ln\,(Forward\_Complexity_i) + \beta_2 \ln\,(intra\_Complexity_i) + \beta_3 \ln\,(inter\_Complexity_i) \; + \boldsymbol{X_i}\,\theta + \alpha_r$$

The third specification assesses the impact of complexity variables with respect to productivity dynamics in the 3 years after 2016:

$$(4) \quad ln\,(productivity_{2019} - productivity_{2016})/productivity_{2016} = \alpha_i + \beta_1 \ln(productivity_{2016}) + \beta_2 \ln\,(Forward\_Complexity_i) + \beta_3 \ln\,(backward\_Complexity_i) + \beta_4 \ln\,(backward\_Complexity_i * Forward\_Complexity_i) \; + \boldsymbol{X_i}\,\theta$$

4. Results

Table 6 shows the results of the baseline model (1) in which it can be seen that forward complexity is always positive and highly significant in all 4 specifications. The first two columns are for GDP per capita with all SLLs (the first one) and eliminating those under 15,000 population (the second one). Similarly, the third and fourth columns show the two samples for productivity. The results show that by level of GDP per capita a positive and significant correlation is found with the presence of business networks, while population size is negatively correlated. For productivity, the only other significant variable besides forward complexity is district in specification 4, which does not consider smaller SLLs.

Table 6: Results of the baseline model with the full and reduced sample

VARIABLES*	(1) GDPpc_all	(2) GDPpc_red	(3) Productivity_all	(4) Productivity_red
forwardcomplexity	0.265***	0.282***	0.176***	0.186***
	(0.0168)	(0.0179)	(0.0102)	(0.0126)
distretto	-0.0342	0.00111	0.0170	0.0285*
	(0.0281)	(0.0232)	(0.0170)	(0.0163)
metropolit	0.151	0.108	0.0524	0.0402
	(0.0968)	(0.0759)	(0.0586)	(0.0533)
pop	-2.88e-07**	-2.63e-07**	-8.55e-08	-8.17e-08
	(1.33e-07)	(1.06e-07)	(8.07e-08)	(7.46e-08)
group	2.57e-05**	2.51e-05***	6.96e-06	6.64e-06
	(1.20e-05)	(9.44e-06)	(7.25e-06)	(6.63e-06)
Constant	-3.748***	-3.743***	10.56***	10.57***
	(0.0595)	(0.0479)	(0.0360)	(0.0337)
Observations	589	501	589	501
R-squared	0.749	0.799	0.783	0.803
Region FEs	YES	YES	YES	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.1 The role of external capabilities

Table 7 shows the results of empirical model (2) in which external capabilities do not appear to play any positive role in determining GDP and productivity levels. This is probably due to the fact that the two measures are highly correlated. This could also explain why we find a negative and significant effect of external capabilities relative to GDP per capita even when we make local and external capabilities interact to control for absorptive capacity.

Table 7: results of empirical model 2 with the full and reduced sample.

VARIABLES*	GDPpc_all	GDPpc_red	Productivity_all	Productivity_red
forwardcomplexity	0.186***	0.273***	0.197***	0.203***
	(0.0126)	(0.0469)	(0.0327)	(0.0335)
backwardcomplexity	-0.125***	-0.0776*	-0.0374	-0.0344
	(0.0480)	(0.0432)	(0.0297)	(0.0309)
Back*Forward	-0.0587***	-0.0575***	-0.00756	-0.0108
	(0.0123)	(0.0134)	(0.00762)	(0.00961)
Constant	10.57***	-3.765***	10.55***	10.56***
	(0.0337)	(0.0474)	(0.0363)	(0.0339)

Observations	501	501	589	501
R-squared	0.803	0.807	0.784	0.804
Region FEs	YES	YES	YES	YES
Control variables	YES	YES	YES	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8 shows the results of empirical model (4) in which the contribution of local and external capabilities to productivity growth is analyzed. Given the data availability, we can only control for a reduced time frame of three years (2016-2019). Moreover, in the first specification productivity growth is studied in two versions: general and of knowledge-intensive sectors as classified by OECD (2016). Here a positive effect of the interaction between external and local capabilities is found with respect to productivity dynamics in all sectors. If only knowledge-intensive sectors are analyzed, then the backward complexity has a direct negative and significant effect, but the forward complexity and interaction have a positive and significant sign with a very high coefficient. These three coefficients added together indicate that a one-point increase in complexity results in a 1.4-fold increase in productivity over the next three years. The availability only for 2016 of data to calculate forward and backward complexity does not allow capturing the dynamic interaction between the two variables, and since these are two closely interrelated phenomena it is not possible to isolate the individual effects. Further verification is needed to get more reliable results. In the next section, however, we see that the positive result of the interaction between local and external capabilities persists even in the GDP levels for capita and productivity once only the most dynamic SLLs are analyzed.

Table 8: Determinants of productivity and knowledge-intensive productivity growth (2016-2019)

	(1)	(2)
VARIABLES*	**ΔProductivity**	**deltaHitech**
lnprod_Base	-0.124***	-4.368***
	(0.0198)	(0.249)
forwardcomplexity	0.0275	1.885***
	(0.0179)	(0.313)
backwardcomplexity	-0.0104	-0.719**
	(0.0161)	(0.302)
Backward*Forward	0.00772*	0.300***
	(0.00450)	(0.0848)
Constant	1.366***	46.05***
	(0.211)	(2.628)
Observations	589	589

R-squared	0.122	0.364
Controls variables	YES	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.2 The role of regional linkages

Table 9 shows the results of model (3) in which the contribution of embedded productive knowledge in networks having different spatial scales is analyzed. Again, the contribution of forward complexity is positive, significant, and stable in all specifications. Embedded knowledge in inter-regional networks also has a positive and significant impact in all specifications. Productive knowledge embedded into intra-regional networks, on the other hand, has a consistently negative and significant coefficient in three out of four specifications. The effect is stronger with the level of productivity than with the level of GDP per capita.

Table 9: The contribution of networks operating at different spatial scales on economic performance

	(1)	(2)	(3)	(4)
VARIABLES*	**GDPpc_all**	**GDPpc_reduced**	**Productivity_all**	**Productivity_reduced**
forwardcomplexity	0.143***	0.229***	0.160***	0.191***
	(0.0535)	(0.0489)	(0.0321)	(0.0341)
interregionalcomplexity	0.164***	0.160***	0.136***	0.125***
	(0.0597)	(0.0546)	(0.0358)	(0.0381)
intraregionalcomplexity	-0.0208	-0.0937*	-0.117***	-0.129***
	(0.0553)	(0.0519)	(0.0332)	(0.0362)
Constant	-3.760***	-3.752***	10.54***	10.56***
	(0.0595)	(0.0477)	(0.0357)	(0.0333)
Observations	589	501	589	501
R-squared	0.753	0.803	0.790	0.809
Region FEs	YES	YES	YES	YES
Control Variables	YES	YES	YES	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

To test for the presence of heterogeneous effects with respect to the degree of development, Table 10 shows the results for SLLs that have GDP per capita and productivity levels below the median (the first two columns), and above the median (the last two columns), respectively. In this case, forward complexity contributes positively only to economic performance above the median (more developed SLLs), while for those below the median (less developed) it is non-significant with a negative coefficient. Participation in interregional networks contributes positively to both groups of SLLs. While intra-regional links have negative and significant coefficient with respect to productivity for SLLs above the median and positive and significant for the determination of GDP levels for SLLs below the median. Finally, as anticipated in the previous section, the interaction between local and external capabilities is positive and significant only for the most developed SLLs and significant and negative for the least developed SLLs.

Table 10: Heterogeneous contribution of networks operating at different spatial scales

VARIABLES*	(1) GDPpc_low	(2) Prod_low	(3) GDPpc_high	(4) Prod_high
forwardcomplexity	-0.0433	-0.000717	0.291***	0.260***
	(0.0746)	(0.0418)	(0.0854)	(0.0615)
interregionalcomplexity	0.222***	0.118***	0.0789	0.114**
	(0.0683)	(0.0370)	(0.0685)	(0.0519)
intraregionalcomplexity	0.134**	-0.0510	-0.000943	-0.149***
	(0.0667)	(0.0368)	(0.0696)	(0.0537)
backwardcomplexity	-0.198***	-0.0543	-0.202***	-0.0981*
	(0.0602)	(0.0330)	(0.0751)	(0.0566)
Backward*Forward	-0.0877***	-0.0438***	0.0769***	0.0278*
	(0.0188)	(0.0115)	(0.0195)	(0.0154)
Constant	-4.031***	10.31***	-3.681***	10.62***
	(0.0817)	(0.0536)	(0.0573)	(0.0411)
Observations	295	295	294	294
R-squared	0.678	0.630	0.454	0.425
Region FEs	YES	YES	YES	YES
Controls	YES	YES	YES	YES

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

These results seem to suggest that the accumulation of increasingly sophisticated knowledge occurs heterogeneously with respect to the degree of development. Less developed SLLs are able to absorb knowledge from less extensive productive networks, such as intra-regional and inter-regional ones. While the impact of international ones is either not significant as in the case of forward complexity, or even negative as in the case of backward complexity. This result, on the one hand, confirms the need for adequate absorptive capacity to capture the benefits of international openness, and on the other, suggests that the strategic coupling between local and external capabilities is a function of network extent and pursues an evolutionary path not only in the accumulation of sectoral but also geographic capabilities.

5. Discussion and Conclusions

This paper has developed an innovative methodology to aggregate productive knowledge embedded in multiscalar networks anchored in each local labor system. In this way, it was possible to link more closely the literature on EEG, which focuses on the study of local capabilities, and that on GVCs or GPNs, which is centered on external knowledge embedded in global networks. Indeed, the distance between these two literatures is also a matter of spatial scale. If our unit of analysis is the national level, these two literatures touch more easily. In fact, in the economic complexity literature, local capabilities are inferred from the ability to export abroad, thus from participation in international networks. Since a large literature points out the huge and growing differences within countries (Iammarino et al., 2018), a more disaggregated level of analysis can help search for the causes. Once the unit of analysis is changed, it opens up the possibility of analyzing how knowledge, embedded in a multiplicity of multilevel networks, contributes to economic performance. A high level of geographic disaggregation such as that of local labor systems (SLLs) appears particularly fruitful for the analysis of local and external capabilities because it allows the two channels to be properly distinguished given that the internal dimension is not assumed ex-ante but derived functionally through commuting flows. To the best of our knowledge, this is the first work that has applied the tools of economic complexity and fitness at the SLL level and decomposed them into several indicators that capture the diversification and sophistication of productive knowledge embedded in multilevel networks. Specifically, the contribution of local knowledge, external knowledge, intraregional and interregional knowledge to the performance of each local labor system was analyzed. The first novel result is that fitness and complexity indicators have a high ability to explain variance in economic performance even at a very granular spatial scale. The Fitness indicator built on the value added embedded in global value chains (forward complexity) obtains similar results in terms of explaining the variance of GDP per capita and productivity than the Employment Complexity indicator, despite being based on an extremely smaller number of sectors (31 vs. 799). Although this work has been applied to only one year (2016) and does not capture the dynamic relationship between the variables, some additional findings seem to suggest new research perspectives: knowledge embedded in the most spatially concentrated networks seems to contribute to the economic performance of the least developed LLSs, while knowledge embedded in more extensive networks contributes to the most developed LLSs. Other findings suggest that external capabilities play a positive role in overall productivity growth and, more strongly, in knowledge-intensive sectors if supported by sufficient absorptive capacity. In addition, once the sample was divided into two groups sorted by the per capita GDP and productivity levels, heterogeneous effects of the different indicators were found. Intra-regional networks have a significant and positive correlation with GDP per capita for SLLs below the median and a significant and negative correlation with productivity for those above the median. Forward complexity is positive and significant for SLLs above the median and negative and non-significant for those below the median. External productive knowledge interacted with forward complexity is positive and significant only for developed SLLs (above the median), while it is significant and negative for less developed SLLs. Finally, knowledge embedded in inter-regional networks seems to play a positive role on productivity independently of the degree of development. These results seem to contribute to the building of a bridge between EEG and GPNs (Boschma, 2022; Rodríguez-Pose, 2021; Yeung, 2021), through the identification of heterogeneous effects, depending on spatial scale, of resources embedded in networks on the ability to create new development trajectories. Multiple production networks organized at different spatial scales can increase regional actor autonomy (Gong et al., 2022) although the contribution of each of these to different levels of local development was not explored yet. In this work, anchoring and absorption of external resources appear to occur when there is an alignment (or coupling) between spatial scale and level of development. This result seems to suggest that the strategic coupling (Coe et al., 2004) of local firms and institutions with complementary or related actors in the GPN also has a spatial scale dimension. Therefore, the opportunity space that constrains places and firms would depend not only on history and place, but also on positioning with respect to different spatial scales. Indeed, at these, an alignment of local capabilities and institutions (in this case approximated by the degree of development) with external resources anchored through a multiplicity of networks can occur.

This analysis has some limitations that are important to point out. First, the availability of input output tables at the Local Labor System level only for the year 2016 does not allow for a dynamic analysis of the interaction between the different variables. This would be even more useful given that the different indicators of spatial complexity are correlated with each other. Second, the limited number of sectors in the input-output tables (31) does not allow for the full exploitation of economic complexity and fitness methodologies. Third, the advantages of using such a disaggregated unit of analysis highlighted in the paper are countered by some disadvantages related mainly to the absence of certain types of data. Indeed, it would be interesting to investigate the relationship of disaggregated complexity indicators at different spatial scales with other characteristics of local labor systems in terms of sustainability, inequality and institutional quality. Some of these limitations can be overcome by comparing results with other places, or by aggregating data at the provincial level. While other limitations, especially those concerning the static nature of the exercise, can be overcome by using time series of input-output tables with more aggregated spatial units. Finally, further development of this work should consider including in the analysis the impact of relatedness density calculated with respect to employment, but also with respect to Input-output flows. These new measures could contribute to the unpacking of the different channels through which knowledge flows and accumulates within and between places connected by a multiplicity of networks operating at different spatial scales. A further step would be to analyze, through the tools of complexity economics, how different geographic scales contribute to horizontal upgrading (in terms of diversification) and vertical upgrading (in terms of sophistication) of places.

Despite these limitations, the results of this analysis seem to support a new dimension in the evolutionary dynamics of places. Not only are sectoral or product capabilities path-dependent and cumulative, but also geographic capabilities that are embedded in different spatial scales. In fact, the ability to benefit from knowledge embedded in geographically expanding networks appears to be correlated with the degree of development. From a policy perspective, this work suggests promoting networking with firms and territories based on specific characteristics in terms of both sectoral and geographic absorptive capacity. Poorer places should focus on positioning in intraregional and interregional linkages to facilitate knowledge absorption, while developed places should focus efforts toward participation and positioning on international networks to anchor external knowledge and foster new development pathways.

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Appendix

Tables 5b: indicator regressions

VARIABLES	(1) lngdpy	(2) lngdpy	(3) lngdpy	(4) lnprody	(5) lnprody	(6) lnprody
VAX	0.417***			0.331***		
	(0.0184)			(0.0112)		
ECIE		0.544***			0.431***	
		(0.0227)			(0.0135)	
forwardcomplexity			0.404***			0.286***
			(0.0149)			(0.0106)
Constant	-3.173***	-5.901***	-3.743***	11.12***	8.956***	10.65***
	(0.0379)	(0.0810)	(0.0147)	(0.0231)	(0.0484)	(0.0105)
Observations	501	500	501	501	500	501
R-squared	0.508	0.536	0.597	0.636	0.670	0.594

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Fig. 4: Forward complexity and GDP per capita (on the left) and productivity (on the right). Colors reflect the macro-regions to which SLLs belong (orange the north of Italy, green the center, and purple the south).

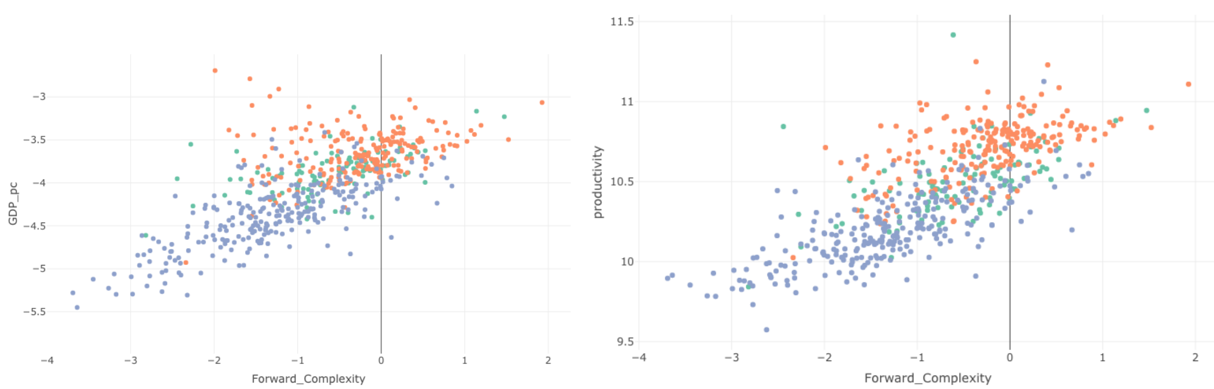

Table 11: Local labor systems sorted by the 4 indicators of complexity

	Forward_Complexity	**ECIE**	**Interregional_comp**	**Intraregional_comp**
1	MILANO	ARZIGNANO	MILANO	MILANO
2	TORINO	LUMEZZANE	ROMA	ROMA
3	ROMA	BERGAMO	BASILICATA	VENEZIA
4	BOLOGNA	BUSTO ARSIZIO	TORINO	TORINO
5	FIRENZE	LECCO	BOLOGNA	BOLOGNA
6	BERGAMO	GRUMELLO DEL MONTE	NAPOLI	BERGAMO
7	GENOVA	CORREGGIO	FIRENZE	MOLFETTA
8	VENEZIA	SASSUOLO	BERGAMO	CORREGGIO
9	PADOVA	THIENE	VENEZIA	NAPOLI
10	BUSTO ARSIZIO	BRESCIA	PADOVA	BARI
11	BIELLA	GUASTALLA	GENOVA	FIRENZE
12	NAPOLI	PORDENONE	BRESCIA	BIELLA
13	CITTADELLA	SCHIO	BUSTO ARSIZIO	PADOVA
14	VERONA	REGGIO NELL'EMILIA	CAGLIARI	BUSTO ARSIZIO
15	BASILICATA	CITTADELLA	BARI	CATANIA
16	BRESCIA	VESTONE	REGGIO NELL'EMILIA	BASILICATA
17	CAGLIARI	MIRANDOLA	COMO	BRESCIA
18	COMO	BOLOGNA	TRENTO	REGGIO NELL'EMILIA
19	UDINE	CASTELFRANCO VENETO	CATANIA	GENOVA
20	NOVARA	CHIARI	PESCARA	LECCO

4.
A multilevel threshold public good perspective on place branding: Evidence from Italy

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This paper proposes a new interpretation of place brand as a Multilevel Threshold Public Good (MTPG) produced by the interaction of narratives from different geographical levels. Using an original dataset of Google trends and tweets from Italian provinces and regions, we test the hypothesis that place branding has a multilevel structure. We further test the MTPG framework applied to place branding, showing that place branding is influenced by different geographic levels which can trigger a spillover in terms of attractiveness if they contribute to crossing a threshold point. The results confirm the presence of a provision point in place branding, showing that the proposed MTPG framework fits the phenomenon. This article contributes to the literature on place branding and brands by providing a new lens for interpreting the phenomenon, which may be useful in better understanding and measuring the interaction of branding strategies operating at different spatial scales.

Keywords: Place Branding, Narrative economics, Multilevel Threshold Public Good, Threshold Regression, Regional Economics.

1. Introduction

"*The destiny of the world is determined less by the battles that are lost and won than by the stories it loves and believes in.*" Harold Goddard (1951, p. 208)

Over the past 30 years, cities have been overwhelmed by global processes that have fostered increased flows of goods, people, and resources. In a context of competition among territories to attract increasingly mobile economic factors, place branding has become one of the most important tools for facing these new challenges. This concept extends the idea of marketing to the promotion of places with the goal of attracting tourists, investment, inhabitants or market flows (Kavaratzis, 2004). Italy is a naturally tourism-oriented country with widespread cultural, artistic and landscape heritage. Tourism contributes between 6 percent and 13 percent of GDP but the concentration of tourism at the local level varies enormously: Rome accounts for 97% of regional tourism, Venice 57%; while in other regions tourism is widespread (Bronzini et al., 2022). Moreover, the effect of tourism on local growth is positive for areas with low value added and low employment, while it is zero for areas that are already heavily touristed. In this context, place branding could be a strategic instrument for recalibrating Italian tourism flows to favor less developed areas.

A virtuous example of place branding policies in Italy has been the project of Matera's candidacy as European Capital of Culture in 2019. Tourism growth in Matera radically accelerated in 2014, from an annual growth rate of about 16% in the previous period (2009-2014) to 31% thereafter (2014-2019) (Padula, 2021). However, this is not always the case: while sometimes large-scale projects and place branding campaigns have an extraordinary impact on the perception of a city, on other occasions they fail to do so. In this article, we ask under what conditions place branding succeeds in creating new intangible assets and increasing attractiveness. In addition, we want to understand how different geographic levels interact in terms of their contribution to place branding and the unfolding of benefits.

The central idea of this analysis is that place brands are produced through place narratives once they become collectively shared. We therefore propose to interpret place brands as Threshold Public Goods (TPGs)-characterized by non-rivalry, non-excludability, and the presence of a provision point. Based on this approach, we expect the effects of place brand provision to occur only after a certain threshold. Furthermore, we consider the multilevel nature of place branding, according to which the provision of a place brand at one geographic level can trigger the provision of the public good at another level, creating spillovers between geographic entities. From this perspective, we propose the new concept of Multilevel Threshold Public Good (MTPG), which is produced by the interaction of narratives from different geographic levels that contribute to exceeding the threshold value. To test this interpretation, we analyze the impact of place branding on tourist attractiveness, as measured by tourist arrivals, considering a panel dataset covering Italian provinces and regions from 2010 to 2019. We regress tourism attractiveness through a Poisson regression model to test the presence of a nonlinear, multilevel relationship between place branding and attractiveness. Indeed, our explanatory variables rely on regional and provincial branding, proxied through an original dataset of Google trends and tweets. In addition, through a threshold regression model (Hansen, 1999), we test whether the MTPG framework can be applied to place branding, showing that the provision of place branding at the provincial level can trigger spillover effects in terms of attractiveness for the whole region when a certain threshold is exceeded, and that regional place branding has positive effects on provincial attractiveness.

This paper proposes several innovative perspectives on place branding: (i) To the best of our knowledge, it is the first study that has an empirical approach to quantifying the impact of place branding on attractiveness; (ii) It provides a new proxy for place branding; (iii) The MTPG framework described below represents a new approach not only in the branding and geography literature, but also in the economics and social science literature more generally; (iv) It enriches the literature on networked and nested place branding (Andéhn and Zenker, 2015) by providing a theoretical framework and methodology for identifying and measuring the different mechanisms through which place branding produces spillovers on attractiveness. This knowledge can provide useful insights for the design of place branding strategies, especially to strengthen the attractiveness of inner areas and territories such as southern Italy.

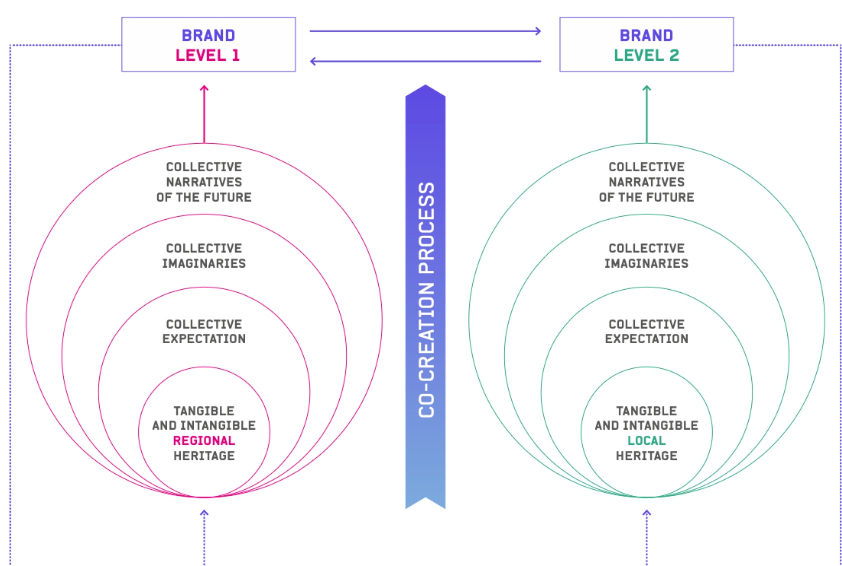
2. Materials and Methods

2.1 Narratives as building blocks of place branding

Over the past two decades, place branding studies have shifted from a normative approach to a cultural one (Ashworth and Kavaratzis, 2009). Anholt (2010) defined place branding as the process of building the brand of a particular place by drawing on its identity and promoting the formation of a positive place image. From this perspective, place branding can be interpreted as an interactive process of collective construction of the meaning of places (Kavaratzis & Kalandides, 2015). Despite these developments, the growing literature on the topic has not reached an agreement on the nature of this process. Recent literature is developing on the analysis of the spatial dynamics of place branding and its multiscale nature (Giovanardi, 2015), highlighting the importance of horizontal cooperation and networked place branding (Zenker and Jacobsen, 2015). Nevertheless, scholars' criticisms that little theoretical refinement seems to have occurred over the past 20 years have raised "the need to rethink place branding" (Ashworth et al., 2015), starting with the open question of what constitutes place branding. Recently, attention has focused on the narrative nature of place branding, emphasizing how place brands are best thought of as narratives or "place stories" (Hansen, 2020). This view locates the main resources used for place branding in the overall "story" of place, which is told by all possible organizations, people, objects, and storytelling devices (Ashworth *et al.,* 2015). Place brands are social constructions: their analysis through the narrative approach is useful for their relationship to language and to how people co-create social reality (Lichrou *et al.,* 2017).

For place branding, the narrative framework must be enriched with two elements: account for its multi-stakeholder structure and its multilevel nature. Indeed, the process of constructing place-based narratives occurs through the spontaneous interaction of a large number of actors: individuals, organizations, public and private institutions, tourists and travelers (Oliveira & Panyik, 2015). The second distinctive feature of place-based narratives is that they influence and are influenced by narratives that operate at different geographical levels. Applying the narrative framework of Vignoli et al. (2020) to place branding, narratives perform four functions: (i) different actors select specific local characteristics of the tangible and intangible heritage (selection); (ii) give conflicting interpretations of their values and meanings (interpretation); (iii) find different causal explanations of story elements (causal modelling); (iv) rationally and emotionally support different behaviors (action support). When narratives become shared and form the image of place (place brand) they succeed in providing causal power. The transition from individual narratives to collective images is sanctioned by a threshold point, beyond which places become more attractive. This process of brand co-creation based on the interaction of narratives produced at different geographical levels produces new intangible public goods, which correspond to new collective meanings and which in turn modify intangible heritage

Figure 1: the narrative framework



2.2 Multilevel Threshold Public Goods Approach to place branding

To further analyze and interpret the geographic characteristics of place branding, the second concept we introduce is based on the Public Goods framework. As mentioned earlier, place brands can be conceived as a (nonrival and nonexcludable) public good at the local level produced by the interaction of narratives. However, local place brands are expected to produce spillover effects and be influenced by the contribution of branding at other geographical levels. In this sense, we can consider place brands as a Multilevel Public Good (MPG), which involves the presence of two or more Public Goods on a different hierarchical level. The literature on MPGs usually considers the presence of individual choice, in which people must choose if allocate their contribution to a global or local good (i.e., Blackwell & McKee, 2003). However, here we want to focus on the peculiar coordination and interaction problems that emerge from the perspective of MPGs governance. Indeed, given the different geographic scales and characteristics involved, it will be crucial to positively manage the externalities created by PGs at different levels. Different spillover dynamics may be present, having potentially direct consequences on the provision and entity of PG at different scales.

Let us consider three different spillover mechanisms between levels, represented through alternative modes of modelling. We will consider a level-1 (such as a region) and a sub-level, or level-2 (such as a province). All mechanisms consider the presence of a particular Public Good at each level. In level-2 we consider a local Public Good, which will only be enjoyable by the individual actor in level-2 who invests in it. In level-1, on the other hand, we consider a global Public Good, so its consequences will be related to all level-2 actors. The mechanisms will differ according to the specific characteristics of the Public Goods considered: whether and when they have a provision point.

Mechanism 1: local PG, global TPG. In the first spillover mechanism, we consider the presence of a local PG and a global TPG. Each level-2 actor can contribute to its own Public Good, which will only have local consequences. However, if the sum of different local contributions reaches a certain threshold, this will trigger a global TPG at level-1, which will be enjoyed by all local actors.

Mechanism 2: local TPG, global PG. In the second mechanism, we consider an opposite dynamic: level-2 actors contribute to a level-1 PG that, given its global characteristics, has consequences for all level-2 actors. Given the supply of the good that the sub-level actors will receive, it could happen that a local TPG is triggered if the local quantity of the good reaches the threshold.

Mechanism 3: local and global TPG. In the third mechanism, we bring the first two mechanisms together. Indeed, there may be situations where a TPG is present at both levels. In this case, we can have a double feedback dynamic, where if the sum of level-2 contributions reaches a certain threshold, a global PG is activated. Moreover, local

PGs have a threshold level in this case, such that if it is reached, a positive spillover effect on the local utility function is triggered.

The three mechanisms sketched in this Multilevel Public Good framework (MTPG), although simple and schematic, are meant to capture some possible characteristics of multilevel governance of Public Goods, emphasizing the importance of recognizing the presence of threshold points that can trigger the provision of goods at different levels how in this sense their provision at one level may influence the provision at a higher or lower level.

Applying the MTPG framework developed here to place branding, we advance two hypotheses based on the previous first two mechanisms (while a different empirical approach needs to be developed for the third mechanism):

Hypothesis 1: *The contribution of provincial branding can have consequences for the entire region if it succeeds in activating a certain threshold in the provision of the level-1 Public Good*.

Hypothesis 2: *Regional branding may contribute to the activation of provincial brands if a certain threshold is exceeded*.

In the rest of the paper, these hypotheses will be tested, using a novel panel dataset introduced in the next section.

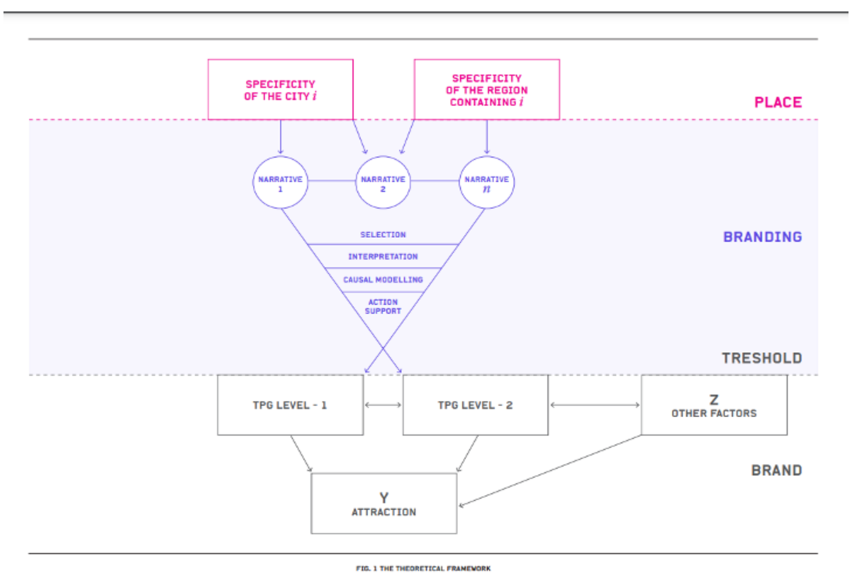


Figure 2: the theoretical framework

2.3 Data

Branding and narratives are not easy to measure. When official statistics are not available, the use of non-traditional data can improve our ability to understand and predict the evolution of complex and new phenomena (Einav and Levin, 2014). In this paper, we use two main sources of non-traditional data to construct a proxy of place branding: Google Trends and Twitter. We develop a 4-steps procedure.

First, as a proxy for consumer interest in places, we use Google Trends related to the name of provinces and regions, which is a daily and weekly real-time index of the volume of queries users enter Google. Indeed, Google queries can be useful preliminary indicators of subsequent consumer purchases (Vosen & Schmidt, 2011).

Second, we use Tweets with the hashtag "#place-name" as a proxy for stories involving a place. Twitter data are popular among social scientists also to detect tourism preferences (Chang & Chu, 2013). Tweets with hashtag #place-name may refer to institutional or informal communications by individual citizens/tourists. When a story is particularly interesting, it may be retweeted by many people, or the same hashtag may be used. In both cases, there is an increase in tweets with the specific hashtag. This measure can properly be used as an indicator of the interest generated by stories involving a specific place. What this indicator does not tell us is whether these stories increase the desire to visit a place or reduce it, or, in the terms of the narrative framework, we do not know whether these stories provide rational and emotional support to concur in the creation of a place brand that increases place attractiveness.

Third, for all these reasons, the interaction between the interest a place generates (number of #place-name) and an indicator that gives us information about the number of future visitors to that place (Google Trends) can give us a raw but reliable indication of the presence of narratives that work in promoting that given place (place-based narrative).

Fourth, as argued in the previous chapters, place-based narratives are the building blocks of place branding, and therefore in the empirical analysis, they are used to investigate the nature and effects of place branding both at the provincial and regional levels:

$$Branding_t = tweets_t \times trends_t \qquad (1)$$

As for aggregating the branding of multiple provinces *i* belonging to the same region *r*, branding is calculated as the interaction of the average number of tweets and trends:

$$Provincial\_Branding_{rt} = \frac{1}{n}\sum_{i=1}^{n} tweets_{it} \times \frac{1}{n}\sum_{i=1}^{n} trends_{it} \qquad (2)$$

Extracting place-related narratives from Twitter has involved scraping existing official Twitter accounts. The scraping was made based on some preliminary criteria coming from specific taxonomy: we selected a list of relevant words and manually converted them into hashtags to be used as input for the Twitter collector. A custom Python program based on the so-called "reverse engineering" method was developed to extract all publicly available tweets from each hashtag. Given the purpose of our analysis, we used the number of Tweets as a variable, relative to each region and province.

We developed a yearly balanced panel dataset based on two different geographical dimensions: provinces (NUTS 3) and regions (NUTS 2). Our dataset covers 17 of the 20 Italian Regions, for a total of 87 out of 110 Provinces between 2010 and 2019. We use the name of Italian provinces and regions as keywords for the scraping of all the relevant tweets and as input for deriving the Google trends. Figure 3 and Table 1 present the descriptive statistics of our relevant variables. It can be observed that although there is a strong correspondence between tweets/trends and arrivals in some geographical areas (such as the province of Rome) it is absent when considering highly tourist areas such as Venice, Bolzano or Trento. On the other hand, regional aggregation gives us a quite different perspective, showing a greater relevance of a region like Tuscany. A more detailed description of the variables considered, and sources can be found in the Appendix.

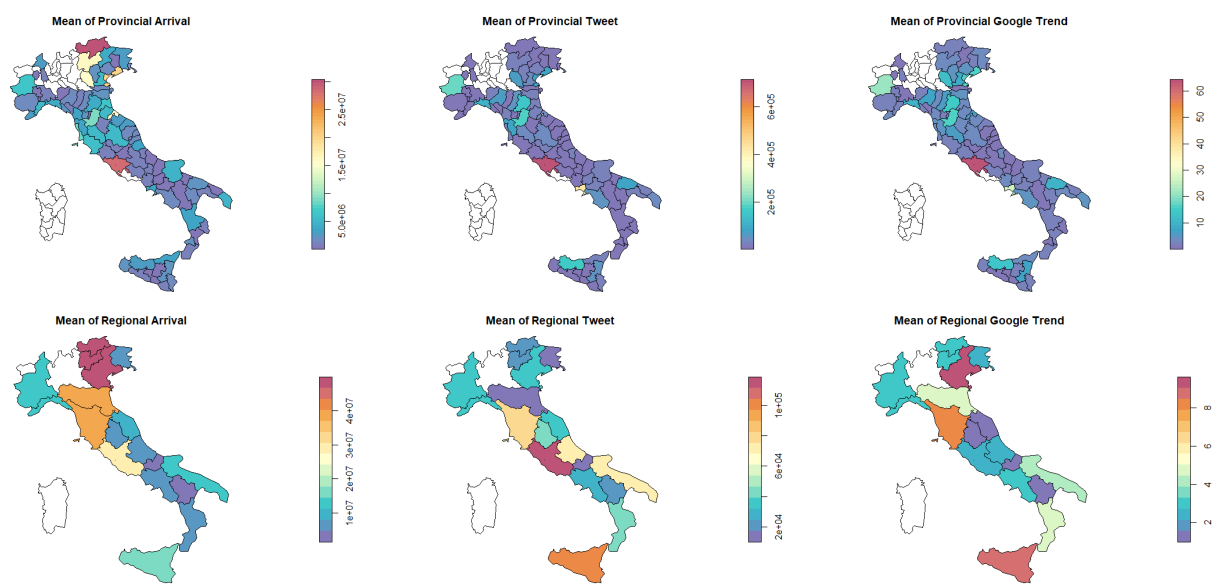


Figure 3: Mean values for provinces and regions of the variables of interest

Table 1: Summary statistics of the variables of interest

Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
Google Trend Province	870	4.417625	7.983345	0	72.16667
Google Trend Region	170	24.22745	26.10775	1.833333	105.8333
Tweet Count Province	870	40040.74	99911.72	11	1082954
Tweet Count Region	170	45469.04	43019.16	111	200432
Provincial Branding	870	877390.5	5209769	0	6.61e+07
Regional Branding	170	1341027	2420198	222	1.26e+07
Provincial Branding (aggregated for Regions)	170	307552.7	771703.2	79.25	4657795
Provincial Arrivals	870	3502784	5382118	52498	3.44e+07
Regional Arrivals	170	1.79e+07	1.58e+07	1346769	5.56e+07

2.4 Empirical strategy

The empirical strategy aims to test hypotheses 1 and 2 developed in the theoretical part using local attractiveness measured by tourist arrivals as a metric of the impact of branding. Specifically, we will use two different empirical models to test whether (i) the relationship between branding and attractiveness is non-linear and involves a multilevel structure; (ii) the multilevel structure is triggered by provision points (thresholds). While the first model specification provides information on the multilevel nature of the branding phenomenon, the second directly investigates the presence of threshold values, corresponding to the Multilevel Threshold Public Good structure introduced earlier. We apply these models to test both hypotheses of our setting: the role of provincial branding on the entire region (mechanism 1) and the role of regional branding on single provinces (mechanism 2). Importantly, mechanism 1 analysis should be considered exploratory because of the number of regions, and thus needs further confirmation to be robust and generalizable.

The first specification relies on a fixed-effect Poisson regression model, considering the count data nature of our dependent variable (*tourist arrivals*). We test for the presence of a nonlinear multilevel relationship between branding and attractiveness by introducing the branding variable in its linear version and its interaction with the branding contribution of the other geographical level. Equation (3) refers to mechanism 1, in which regional arrivals are regressed with respect to regional branding and the branding contribution of the provinces which belong to that given region (refer to the previous section for details on these two indicators). Similarly, to test mechanism 2, equation (4) considers the role of both provincial and regional branding on provincial arrivals, as well as their interaction. In this way, both specifications refer to the idea that branding can be provided by different geographical levels, as well as the possibility of having synergies or trade-offs between the branding contribution at different levels.

$$Regional\_Arrivals_{rt} = \exp\,(\beta_1 Provincial\_Branding_{r,t-1} + \beta_2 Regional\_Branding_{r,t-1} + \beta_3(Provincial\_Branding_{r,t-1} \times Regional\_Branding_{r,t-1}) + \boldsymbol{X_{r,t-1}}\theta + \alpha_r + \gamma_t) \qquad (3)$$

$$Provincial\_Arrivals_{it} = \exp\,(\beta_1 Provincial\_Branding_{i,t-1} + \beta_2 Regional\_Branding_{i,t-1} + \beta_3(Provincial\_Branding_{i,t-1} \times Regional\_Branding_{i,t-1}) + \boldsymbol{X_{i,t-1}}\theta + \alpha_i + \gamma_t) \qquad (4)$$

Where $\boldsymbol{X_{t-1}}\theta$ represents the vector of control variables (GDP per capita, institutional quality and population density), γ_t is the time fixed-effects, and α_i is the fixed effects at the regional or provincial level according to the different specifications and as specified by the different subscripts (*i* for the provinces, *r* for the regions). Including fixed-effects in our regression specification allows us to control for unobserved heterogeneity and time-invariant characteristics of regions/provinces, such as geographical features or cultural characteristics. All independent variables are considered in their lagged specification.

The second empirical specification investigates the presence of a provision point, using a specific model to test and estimate the presence of a threshold in our relationship. We apply Hansen's (1999) panel threshold fixed-effect model to our dataset. This model identifies the presence of a structural break in the relationship between variables, capturing the presence of endogenous threshold effects and estimating their values. Thus, instead of introducing an artificial threshold in the model, this specification estimates the presence of a point of discontinuity in the variables and tests its statistical significance. Starting from mechanism 2, this model is applied to our setting to estimate whether the provision of a regional public good (brand) can contribute to the creation of the provincial public good and trigger an effect on provincial attractiveness. In our framework, the provision of regional brands can have positive spillovers to the provincial level: when regional branding reaches a certain threshold, it can trigger an effect on provincial branding. We then expect the relationship between provincial branding and province attractiveness to be nonlinear and split into two different regimes, depending on regional branding. To apply this model in a linear context, instead of considering the number of arrivals as the dependent variable, we will consider the difference in arrivals between time *t* and *t-1*. The mechanism can be written as:

$$\left(Provincial\_Arrivals_{i,t} - Provincial\_Arrivals_{i,t-1}\right) = \alpha_i + \beta_1 Provincial\_Branding_{i,t-1} + \boldsymbol{X_{i,t-1}}\theta,\ \ if\ Regional\_Branding_{i,t-1} \le \delta \qquad (5)$$

$$\left(Provincial\_Arrivals_{i,t} - Provincial\_Arrivals_{i,t-1}\right) = \alpha_i + \beta_2 Provincial\_Branding_{i,t-1} + \boldsymbol{X_{i,t-1}}\theta,\ \ if\ Regional\_Branding_{i,t-1} > \delta \qquad (6)$$

Where δ represents the level of the threshold. Introducing a dummy variable in the model, we can rewrite it through a single expression, as:

$$\left(Provincial\_Arrivals_{i,t} - Provincial\_Arrivals_{i,t-1}\right) = \alpha_i + \beta_1 Provincial\_Branding_{i,t-1}\, I\, (Regional\_Branding_{i,t-1} \leq \delta) + \beta_2 Provincial\_Branding_{i,t-1}\, I\, \left(Regional\_Branding_{i,t-1} > \delta\right) + \boldsymbol{X_{i,t-1}}\theta \quad (7)$$

where β_1 and β_2 represent the parameters of interest capturing the effect of the branding on the attractiveness below and above the threshold defined on the regional branding respectively. In the same way, we will estimate mechanism 1, expressed by:

$$\left(Regional\_Arrivals_{r,t} - Regional\_Arrivals_{r,t-1}\right) = \alpha_i + \beta_1 Regional\_Branding_{r,t-1}\, I\, (Provincial\_Branding_{r,t-1} \leq \delta) + \beta_2 Regional\_Branding_{r,t-1}\, I\, \left(Provincial\_Branding_{r,t-1} > \delta\right) + \boldsymbol{X_{i,t-1}}\theta \quad (8)$$

Table 2: Results for the fixed-effect Poisson models for the Mechanism 1; p-values in parenthesis

Dependent Variable: Regional Arrivals				
Variable	(1)	(2)	(3)	(4)
Provincial_Branding$_{t-1}$	-3.31e-05 (0.291)	-4.98e-05 (0.007)	-4.55e-05 (0.053)	-5.13e-05 (0.005)
Regional_Branding$_{t-1}$	7.08e-05 (0.082)	-6.07e-05 (0.016)	2.19e-05 (0.370)	-6.61e-05 (0.002)
Provincial_Branding$_{t-1}$ × Regional_Branding$_{t-1}$	9.83e-11 (0.068)	1.16e-10 (0.000)	1.48e-10 (0.002)	1.10e-10 (0.001)
GDP Per capita Region$_{t-1}$			15.13524 (0.000)	1.3237923 (0.707)
Regional Institutional Quality$_{t-1}$			0.00181444 (0.994)	0.21801533 (0.114)
Regional Population Density$_{t-1}$			0.0015549 (0.129)	0.00131969 (0.047)
Province Fixed Effects	YES	YES	YES	YES
Time Fixed Effects	NO	YES	NO	YES
Number of observation = 153		**Number of groups = 17**		

3. Results

Table 3: Results for the fixed-effect Poisson models for the Mechanism 2; p-values in parenthesis

Dependent Variable: Provincial Arrivals				
Variable	(5)	(6)	(7)	(8)
Provincial_Branding$_{t-1}$	-4.75e-06 (0.000)	-3.33e-06 (0.000)	-4.94e-06 (0.000)	-3.39e-06 (0.000)
Regional_Branding$_{t-1}$	7.91e-05 (0.008)	-4.18e-05 (0.150)	6.93e-05 (0.018)	-4.44e-05 (0.131)
Provincial_Branding$_{t-1}$ × Regional_Branding$_{t-1}$	1.11e-11 (0.000)	8.14e-12 (0.000)	1.20e-11 (0.000)	8.57e-12 (0.000)
GDP Per capita Province$_{t-1}$			1.0097213 (0.000)	0.28608082 (0.076)
Province Institutional Quality$_{t-1}$			-0.09797205 (0.236)	-0.0943118 (0.045)
Province Population Density$_{t-1}$			0.00016448 (0.413)	0.00001771 (0.888)
Province Fixed Effects	YES	YES	YES	YES
Time Fixed Effects	NO	YES	NO	YES
Number of observation = 783		**Number of groups = 87**		

Table 2 and Table 3 show the results for the Poisson model with respect to the impact of branding on regional attractiveness (mechanism 1) and provincial attractiveness (mechanism 2) respectively. We present results for several specifications, introducing time fixed effects and controls only in some specifications. These models aim to test whether attractiveness can be explained not only by direct branding strategies, but also by the branding contribution of other geographic levels and how these two different levels of contribution interact. The terms measuring the direct effect can be read as the presence of place branding policies created from scratch, not in connection with the branding network at different spatial scales. By analyzing the first mechanism in the specification without controls or time fixed-effect (specification (1), Table 2), we see how the model fails to find a direct positive impact of the sum of provincial branding and regional branding on regional attractiveness, but instead finds a positive and significant impact of the interaction between provincial and regional branding: regional attractiveness is thus influenced by a synergy between branding operating at different geographic levels. Adding the control variables (specification (3) and (4), Table 2) and the time fixed-effects (specification (2) and (4), Table 2), the interaction of branding across geographic scales remains significant and positive, while the direct effects are not stable and do not provide definitive results. In the second mechanism (Table 3), the presence of possible geographic synergies is even more pronounced: the interaction term between local and regional branding turns out to be highly significant as an explanatory variable of provincial attractiveness. Adding the control variables (specification (7) and (8), Table 3), the direct effect of regional branding on provincial attractiveness is not stable and changes sign, while the direct effect of provincial branding remains significant and negative. This result can be interpreted as the presence of branding policies disconnected from the network of local meanings and thus perceived as artificial and detrimental to attractiveness.

The second specification, relative to both mechanisms, directly examines the presence of a threshold point in brand provision through Hansen's threshold regression model. The results reported in Table 4 show the estimation for a threshold point, which tests whether the influence of regional branding on regional attractiveness depends on the specific branding contribution regime at the provincial level. Table 5 reports the results for mechanism 2, testing if provincial branding is regime dependent on regional branding. Through this model, we test whether the concept of Multilevel Threshold Public Good can be applied to this phenomenon. The results are in line with our hypotheses: for both mechanisms, the presence of a threshold point is significant according to our model. Specifically, in the first mechanism, the provincial contribution to regional branding strategies leads to the presence of two regimes in influencing regional attractiveness (p-value of threshold point: 0.013). Before the threshold point, regional branding strategies do not have a significant influence on arrivals to the region. In contrast, above the threshold point, regional branding succeeds in having a positive and significant impact on attractiveness. Similarly, in mechanism 2, the presence of two different regimes in the impact of provincial branding on provincial attractiveness also appears significant and determined by the contribution of regional branding (p-value of threshold point: 0.005). In this case, the lower regime-which precedes the achievement of the threshold is found to be significant but with a negative coefficient. While in the upper regime, the impact of provincial branding has a positive and significant influence on tourist arrivals in the province. This result confirms that of Poisson's model, in which provincial branding policies disconnected from other spatial scales may even be detrimental to local attractiveness.

Table 4: the tables indicate the result of the equation (8) with respect to the threshold estimation and the threshold regression analysis

Threshold variable: Regional_Branding$_{t-1}$	**Threshold**		**[95% conf. interval]**	
	221461.3281		209495.00	221461.3281

Threshold effect test (bootstrap = 1000)	RSS	MSE	F-Stat	Probability
	3.12e+13	4.03e+10	63.11	0.0050

Dependent Variable: Provincial Arrivals (difference)	Coefficient	Robust Standard Error	t	P>|t|	[95% conf. interval]	
GDP Per Capita Province$_{t-1}$	9731024	956275.8	10.18	0.000	7830011	1.16e+07
Province Population Density $_{t-1}$	1619.985	852.5762	1.90	0.061	-74.880	3314.85
Provincial Institutional Quality $_{t-1}$	121692.2	183965.8	0.66	0.510	-244019.6	487404
Provincial_Branding $_{t-1}$						
Regional_Branding $_{t-1}$ ≤ threshold	-0.0212907	0.0091462	-2.33	0.022	-0.03947	-0.00311
Regional_Branding $_{t-1}$ > threshold	0.0108739	0.0053915	2.02	0.047	0.000156	0.02160
Constant Term	-638771.9	234068.7	-2.73	0.008	-1104085	-173458.6
Fixed-effects (within) regression **Number of groups** = 87			**Number of observation** = 783 **Observation per group**= 9			
R-squared: Within = 0.1543		**Between = 0.1165**			**Overall = 0.0575**	
F(5,86) = 1697.64			**Prob > F** = 0.0000			

Table 5: the tables indicate the result of the equation (7) with respect to the threshold estimation and the threshold regression analysis

Threshold variable: Provincial_Branding$_{t-1}$	**Threshold**	**[95% conf. interval]**	
	298453.8438	295920.2188	318848.3438

Threshold effect test (bootstrap = 1000)	RSS	MSE	F-Stat	Probability
	5.41e+13	3.76e+11	20.56	0.0130

Dependent Variable: Regional Arrivals (difference)	Coefficient	Robust Standard Error	t	P>|t|	[95% conf. interval]	
GDP per capita Region$_{t-1}$	1.06e+08	4.90e+07	2.17	0.046	2213670	2.10e+08
Region Population Density $_{t-1}$	27424.28	7048.904	3.89	0.001	12481.27	42367.29
Regional Institutional Quality$_{t-1}$	-475865.7	1870803	-0.25	0.802	-4441792	3490060
Regional_Branding $_{t-1}$						
Provincial_Branding $_{t-1}$ ≤ threshold	0.051828	0.3163765	0.16	0.872	-0.618860	0.7225163
Provincial_Branding $_{t-1}$ > threshold	3.959254	0.4903948	8.07	0.000	2.919663	4.998844
Constant Term	-8347498	3199665	-2.61	0.019	-1.51e+07	-1564512
Fixed-effects (within) regression **Number of groups** = 17			**Number of observation** = 153 **Observation per group**= 9			
R-squared: Within = 0.1928		**Between = 0.0302**			**Overall = 0.0113**	
F(5,16) = 38.79			**Prob > F** = 0.0000			

4. Discussion

This paper discussed place branding from a new perspective. On the one hand, we read the concept through the narrative framework. On the other hand, we argued that place brand is an intangible public good, characterized by the presence of a provision point and spillovers among different geographic entities. These spillovers refer to narratives from different spatial scales that can contribute to the achievement of the critical mass (threshold value) necessary for the provision of the good. In branding terminology, the interaction between narratives produced at different geographic levels can reinforce collective narratives with the function of constructing new images of a place. We hypothesized that this Public Good is found at different hierarchical levels. Specifically, we sketch three simple but illustrative mechanisms, characterized by the presence of different Public Goods, depending on their geographical impact and their provision function (linear or with a provision point).

This framework was tested using two different specifications applied to a novel panel dataset involving Italian provinces and regions. The first (a fixed-effect Poisson model) simply tests the influence of multilevel branding strategies on place attractiveness. The results of this specification show that place branding is a multilevel phenomenon through which the presence of branding contributions at different geographic levels is essential for increasing both provincial and regional attractiveness. The direct effect of both provincial and regional branding is less clear from our results. The only case where a negative and stable effect is found is the direct impact of provincial branding on provincial attractiveness. This evidence seems to confirm that place brands are formed in the interrelationship of systems of geographic abstractions based on different spatial scales (Andéhn and Zenker, 2015). The presence of branding policies disconnected from the network of local meanings may be perceived as artificial and detrimental to attractiveness. The second model implemented aims to verify and estimate the presence of a threshold point in the impact of branding over attractiveness, defining the threshold in a multilevel setting. The results confirm the presence of a provision point in the creation of place branding: the effect of place branding can be triggered and influenced by the branding contribution of other geographic scales. In this sense, the Multilevel Threshold Public Good framework seems to fit the phenomenon.

Our analysis has some limitations that are important to point out. First, the use of raw data does not allow us to disentangle the contribution of top down (institutional) place branding from that of bottom up place branding. Second, the Mechanism 1 analysis must be considered exploratory because of the small number of regions. Third, this paper examines only one dimension of the impact of branding (tourism attractiveness), without considering other aspects such as population flows, investment and other market goods. Finally, given the empirical strategy adopted and the availability of data, we could only test the first two mechanisms of those proposed in the theoretical framework. Although the variables used can be further refined and the empirical strategy expanded, the results obtained provide important insights for scholars and policy makers. Indeed, the new approach to place branding proposed in this paper shows two key features of this phenomenon, which can open up new evaluations and analyses: its multilevel aspect-which can determine the presence of synergies and trade-offs between different contributions to branding-and its nonlinear structure, described here through a public good characterized by the presence of a provision point. From a policy perspective, the results of this work suggest that integrated and networked branding policies should be promoted at multiple levels in order to maximize positive externalities and not get trapped below threshold values. Moreover, focusing place branding interventions in lagging areas or lesser-known places in Italy would have a twofold positive effect: supporting their growth and encouraging the decongestion of those negatively affected by overtourism.

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Appendix

Data sources

The Google trend data for 2010-2019 were downloaded from https://trends.google.it/. The numbers provided by the platform represent the search interest in relation to the highest point on the graph for the region and period indicated. A value of 100 indicates the highest search frequency for the term, 50 indicates half of the searches. A score of 0, on the other hand, indicates that not enough data were found for the term. In order to make all the data comparable, we downloaded them by anchoring them to the search term ‘Rome’ (the highest in terms of searches). Google trends only allows downloading 5 places at a time, so we always included the city of Rome and changed the other 4 destinations each time. In this way we downloaded data on all provinces and regions. The data provided were monthly. We aggregated them by year through the average and gave them the value 0 in the case of <1 *searches.* The name of each province and region was downloaded as a generic search term. Only in the cases of names corresponding to other meanings (Brindisi, Como, Fermo, Lecco, Lodi, Potenza, Prato and Trapani) were the data for the search term ‘Comune italiano’ downloaded. For regions with compound names, the full name was compared with the abbreviated name (e.g. Friuli Venezia Giulia with Friuli), and the search term with the highest data was used. Also in the case of compound provincial names (e.g. Barletta Andria Trani) the search term with the highest data was chosen.

Data on tourist arrivals 2010-2019 were downloaded from http://dati.istat.it/ in the section "Arrivi, presenza, permanenza media-mensili". The monthly statistics on the movement of customers concern only accommodation establishments. We summed up the presences in all types of accommodation establishments and aggregated them over the 12 months.

The data on GDP NUTS-3 2009-2018 were downloaded from EUROSTAT https://ec.europa.eu/eurostat/web/rural-development/data.

Data on the resident population 2010-2019 were downloaded from https://demo.istat.it/. And the surface area data to calculate density were taken from www.tuttaitalia.it.

Data on institutional quality are provided by the work of Nifo & Vecchione (2014).