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The nature and the strength of agglomeration drivers and their technological specificities

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The nature and the strength of agglomeration drivers and their technological specificities

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Abstract

This paper delves into geographical agglomeration patterns of economic activities focusing on the connection between these agglomeration tendencies and sectoral patterns of innovative activities. Within a broad evolutionary perspective, we refine upon incumbent statistical models, trying to distinguish between intra- and inter-sectoral agglomerative forces, conditional on different types of sectoral innovative activities. Utilizing data spanning three distinct years, a decade apart, we investigate the systematic nature of spatial distributions, the relationship between agglomeration drivers and technological paradigms, and shifts in agglomerative tendencies over time.

Our findings suggest that economic space is far from uniform, but the spatial heterogeneity differs across sectors as it is driven by various factors, including increasing returns, urbanization advantages, and sector-specific forms of knowledge generation and diffusion.

Keywords: spatial agglomeration, evolutionary economic geography, increasing returns, externalities, knowledge specificities, Pavitt taxonomy.

JEL: E12, E25, P16, C67, O14

1 Introduction

Evolutionary economics, originally centered around the study of sources, procedure, and effects of innovation has significantly advanced our understanding of technological and industrial dynamics (e.g. the seminal contribution by Freeman (1982); Nelson & Winter (1982); but the field has expanded, see Dosi (2023)). However, the spatial aspects of these evolutionary dynamics remained relatively underdeveloped, notwithstanding recent advances in evolutionary economic geography (e.g. Boschma (2017); Castaldi et al. (2017); Frenken et al. (2007) among others) and few empirically verifiable statistical models (inlcuding Bottazzi et al., 2007; Bottazzi & Gragnolati, 2015).

Moreover, although there is an increasing understanding of the heterogeneity of entities and innovative drivers across sectors, the empirical analysis of agglomerative forces has yet to explicitly consider the technological specificities of various sectors. This study aims to bridge this gap by examining such heterogeneity in terms of sectoral and location-wide agglomerative drivers.

We address three intertwined questions concerning the spatial agglomeration of economic activities.

First, we examine the spatial distribution of economic activities, studying whether it exhibits systematic and potentially self-reinforcing structures or is merely random. If systematic, what drives these agglomeration patterns?

Thus, second, how do agglomeration drivers relate to the learning features distinctive to particular technological paradigms and specific sectors in which they are nested?

Third, granted the above, have agglomeration tendencies strengthened or weakened in the most recent period?

A model in evolutionary spirit capable of distinguishing between intra- and inter-sectoral agglomerative forces is employed to explore the relative importance of sector-specific agglomeration economies compared to 'general' location-specific ones, refining upon Bottazzi et al. (2008). Our findings indicate the prevalence of agglomerations among firms within the same sector (at a 3-digit disaggregation level), especially in some technology-specific groups of sectors.

Concurrently, we construct a simple test to ascertain the significance of these agglomeration drivers.

Further, we link the strength of the drivers of location with Pavitt's taxonomy deepening our understanding of the nexus between agglomeration forces and *patterns of innovative activity*.

Finally, this exercise is replicated for three distinct years, a decade apart, to discern potential shifts in agglomerative tendencies over time and shed light on their temporal evolution.

The next sections are structured as follows. Section 2 nests the discussion of opportunity forces in the analysis of technological change and the implied nature of returns, while section 3 places this theoretical discussion within the history of spatial literature. Section 4 presents the data for empirical analysis. Section 5 details the multi-site location models in three configurations, including the Null Model used for hypothesis testing. Section 6 discusses the empirical analysis results.

2 Technological knowledge and increasing returns

It is intuitive that the existence of agglomerative phenomena implies some form of spatially nested increasing returns at some level – e.g., firm-level, industry-level, or across industries. However, one is rarely explicit on their sources and extensions and their implication in terms of properties of equilibria, if any.

Indeed, it is crucial to first understand their sources. Suppose that they are mainly pecuniary ones, associated, say, with transport costs, etc. It is plausible in these circumstances to think of countervailing forces curbing such an increasing return process, linked to e.g. congestion, increasing land rents, rivalry in the allocation of local 'scarce' resources, etc. If the latter step is early enough, one might think that they can still come together with some notion of conventional equilibrium.

A totally different story concerns all these environments wherein increasing returns stem from knowledge accumulation. Knowledge in analogy with sheer information involves an extreme form of increasing returns. Unlike normal commodities, the technical information can be used independently of the scale of production and also by other producers (Arrow, 1996; Dosi, 2023, for further discussions). The low marginal cost of reproduction and distribution makes it difficult to exclude others from having access to newly generated information unless there are politically constructed legal constraints (e.g. IPR).

Moreover, the cumulative nature of knowledge accumulation accentuates such increasing returns: knowledge builds upon itself, thus involving what economists call *dynamic increasing returns*. That is, in the physicists' parlance, they are 'non-conservative systems'. But this is not because they 'dissipate' energy to the outside, but because they 'create energy' ex nihilo from within – something clearly in violation of physical laws, but not of socio-economic evolution(more in Dosi, 2023).

There are analogies as well as differences between information and technological knowledge.

Sheer information is footloose and nowadays essentially spaceless. Sitting in the middle of nowhere on may well download on its computer the blueprints of the most complicated technologies. However, understanding them is another matter, and even more so implementing them. The latter activities involve *knowledge as distinct from information*. Such knowledge is embodied in people and more often in organizations, which ought to be considered as problem-solving entities characterized by different technological and organizational capabilities. Hence, their technological activities tend to develop incrementally from what they already know, even when seeking incremental changes, making innovation and imitation often indistinguishable (Pavitt, 1987).

Essentially, the common features between information and knowledge highlighted by what we call the Stanford-Yale-Sussex synthesis (Dosi, 2023) entail the non-rivalry, indivisibility, potential "scale-freeness," and the increasing returns properties both in their utilization and their accumulation over time. All this stands

very uneasily with any kind of General Equilibrium.
As Arrow (1996) emphasizes,
'[c]ompetitive equilibrium is viable only if production possibilities are convex sets, that is do not display increasing returns,' but ... 'with information constant returns are impossible' (p. 647).
'The same information [can be] used regardless of the scale of production. Hence there is an extreme form of increasing returns.' (p. 648)
Granted that a crucial issue regards the domain in which such increasing returns are located.
In this respect the debate around increasing returns concern also their extension. Indeed, Alfred Marshall was one of the first to distinguish between economies internal to a particular firm and the economy-wide increasing returns resulting from the progress of the general economic environment. The former case is clearly incompatible with the ' atomless' micro condition for a general equilibrium. But, what about the latter? As already noted by Sraffa (1926), the only circumstances where a competitive *partial* equilibrium, with the canonic demand curve going down and the supply one going up, might hold is that whereby increasing returns are external to the firms but internal to the industry. Formally, in order to assume a (slightly) decreasing industry supply curve maintaining "U" shaped firms supply curve, we must have an infinite number of firms with consecutive cost curve's minimum point on the same industry supply line [1]. Well beyond the technical drawbacks of the assumption, empirically this is the case that one encounters most rarely, as Marshall himself recognizes: "the economies of large-scale production can rarely be allocated exactly to a single industry: they are largely tied to groups, often large groups, of related industries." In fact, even more generally Young (1928), and earlier Adam Smith argued on the general increasing returns property of the division of labor as it leads to new inventions, both because workers engaged in specialized operations develop better routines for the same tasks, and, together the decomposition of complex processes into a succession of simple one, are more easily amenable to the use of machines. However, the division of labor is limited by the extent of the market: "It would be wasteful to make a hammer to drive a single nail" (Young, 1928, p.530). In turn, the extent of the markets involves also the growth of related industries and thus a generalized increasing division of labor. This observation (i.e., production capacity depends on the division of labor, which in turn depends on the overall production capacity of the economy), has far-reaching consequences. It implies that every "invention" potentially triggers alterations in the industrial activity of other industries, propagating cumulatively. In this perspective, one can hardly assume the existence of increasing returns internal to a single industry, and, at the same time, external to single firms.
Note that the dynamic increasing returns associated with an increasing division of labor can hardly be squeezed under the heading of 'externalities'. Rather, they are one of the instantiations of the process of technical change and innovation unfolding over time, with many such processes entailing also knowledge

[1] This problem could be partially overcome on the ground of the Dixit & Stiglitz (1977) model of product differentiation.

complementarities and spillovers which one specific to individual sectors or clusters of them (the case of Silicon Valley comes immediately to mind).
All the forgoing dimensions bear implications also in terms of the possible drivers of agglomeration.
At one extreme suppose that all 'externalities', or, dynamically, all the dynamics of knowledge accumulation are internalized within single firms. In this case, any possible spatial differentiation ought to stem from the 'intrinsic attractiveness' of a particular location (ranging from some local natural resources all the way to universities generating specific forms of knowledge), and from the pattern of diversification of the firms placed in those particular locations.
At the opposite extreme, think of the spatial nestedness of the generation of technological knowledge by the ensemble of firms present in any particular location, mastering specific technologies or clusters of them. In this case, it could well be that areas that were originally indistinguishable, progressively differentiate via path-dependent processes through which seemingly 'small' random events, say the location of particular firms, self-amplify via knowledge spillovers and their accumulation over time. This phenomenon is empirically likely due to two linked features of technological knowledge, namely its pragmatic nature and its degrees of tacitness. Indeed, most technological knowledge has a pragmatic nature in the sense that it is accumulated through experience in search, production, and use - through "learning by searching", "learning by doing" and "learning by using". Relately it involves at least some degree of tacitness, in the sense that cannot be completely codified and transformed into sheer 'information'. This leads to the fact that personal contacts, training, and experience, are essential for effective technological learning (Pavitt, 1987). Obviously, face-to-face contact and labor mobility are facilitated by the spatial proximity of firms.
Needless to say, empirically one is likely to observe combinations between the two foregoing archetypes. However, the big challenge, which we shall begin to address in the following is to detect the relative importance of the two types of drivers in the observed combinations between areas and sectors.
So far we have mainly discussed supply-side (mainly technology-related) dynamics. This does not mean that demand factors are irrelevant. They are indeed quite important, first, at a more macroeconomic level through the Keynesian-Kaleckian demand-led mechanism of growth and the process of incremental specialization illustrated above.
Second, they matter a lot also at the spatial level whenever local demand flows are associated with user-producer knowledge exchanges via "learning by interacting". Third, demands interdependences are at the core of urbanization phenomena also characterized by the local specificity of activities that are not tradeable over long distances, e.g. many services.

3 The state of the art

Marshall's pioneering work marked the inception of spatial considerations in economic analyses. His insights, particularly on industrial agglomeration drivers, remain foundational. In the *Principles of Economics* (Marshall, 1920), Marshall posited that industries specialize geographically due to the advantages of spatial proximity, such as reduced transport costs and 'efficient' labor markets, whatever that means. Moreover, he notably anticipated the role of knowledge spillovers in the emergence of industrial districts by emphasizing accelerated knowledge transmission in spatially concentrated industries, but also facilitated the recombination of ideas into novel forms:

"When an industry has thus chosen a locality for itself, it is likely to stay there long: so great are the advantages which people following the same skilled trade get from near neighbourhood to one another. The mysteries of the trade become no mysteries; but are as it were in the air, and children learn many of them unconsciously. Good work is rightly appreciated, inventions and improvements in machinery, in processes and the general organization of the business have their merits promptly discussed: if one man starts a new idea, it is taken up by others and combined with suggestions of their own; and thus it becomes the source of further new ideas."
(Marshall, 1920, p. 156).

While Marshall's work was groundbreaking, geographical economic analyses were originally predominantly shaped by neoclassical-inspired theorists for a considerable period. Therefore, it is not surprising that economics for several decades has overlooked the analysis of industrial agglomerations, conceiving geographical-economic analyses as the optimal firm location-decision given the position of raw material, market, and the transport costs (Christaller, 1933; Hotelling, 1929; Losch, 1940; Von Thünen, 1826; Weber, 1909). The incompatibility between the increasing returns and the convexity assumption necessary to assume an equilibrium framework has been long neglected until the Dixit & Stiglitz (1977) model enabled the modeling of imperfect competition, paving the way for the inclusion of some form of increasing returns although of a very limited kind.

The 1990s witnessed the birth of New Economic Geography (NEG), which aims to formalize insights from spatial economics (Krugman, 1991, 1998), incorporating increasing returns basically stemming from localized pecuniary externalities. Often, "New" theories (New Growth, New Trade, New New Trade...) are all exposed to the stretching tension between the effort to incorporate some form of spatially localized increasing return and a General Equilibrium analysis whose properties are bound to rest upon the absence of increasing returns (Arrow, 1996). The conflict is particularly acute regarding pure external economies, especially knowledge dynamics which, as we have seen above, entail an extreme form of increasing returns. As such, it sits very uneasily with any kind of General Equilibrium. Thus, to maintain the latter, many NEG economists questioned the validity of explanations anchored in knowledge spillovers; some argued against their measurability, drawing upon the empirical support of those challenging their existence (see Breschi & Lissoni, 2001). To remain in an equilibrium perspective, NEG economists easily include in the analysis of agglomerative forces only pecuniary externalities, such as the benefits of proximity to inputs or the sharing of labor pooling, which act exclusively through prices, thus allowing for counterbalancing effects given e.g. shortages that limit the persistence of increasing returns themselves.

Nevertheless, the pronounced concentration of production clusters in areas distant from major urban centers and transport infrastructures suggests the influence of dynamics beyond mere transport costs or localized demand (more on that below, but see Ellison & Glaeser, 1997; Maurel & Sédillot, 1999). Spatial concentrations in specific industrial sectors do not always indicate direct commercial ties within the same region (McCann, 1995). These observations challenge the sole reliance on pecuniary externalities for explaining agglomeration, as favored by NEG scholars. Instead, they underscore the significance of localized information and knowledge flows. Quite independently, the second half of the 20th century saw a growing emphasis on the endogenization of technological change in growth models –i.e the "residual" of Abramovitz (1956) and Solow (1957)– leading to discussions on the economic implications of *learning by doing* (Arrow, 1962) and *increasing returns* to knowledge (Romer, 1986). Moreover, Jane Jacobs' analysis of the city's economy comes from that period, leading to the notion of Jacobian spillover. The Jacobian idea of spillovers is often opposed to the Marshallian one. Jacobs (1969), argues that the main sources of knowledge exchange come from outside the company's industry. Therefore, she emphasizes the importance of the variety and diversity of geographically close industries –rather than specialization– to promote innovation and growth. According to her theory, cities are the main places of innovation thanks to their industrial diversity: the variety of sectors within a geographical region favors knowledge recombination, stimulating innovative activity and economic growth. Indeed, Jacobs' perspective is at the core of the urbanization theory of agglomeration.

During roughly the same period in Italy, the Marshallian view of the economy was brought back to the attention of the scientific community by Becattini and colleagues (Becattini et al., eds. 2014). The resurgence of the debate around industrial districts was undoubtedly due to the controversial role of the small firm in the Italian economy, whose efficiency and competitiveness could not be explained by the dominant theoretical framework of those years. According to a long established view, which we personally do not fully reject, the advantages of division of labor and automation could only be achieved by means also of large factories. Conversely, small firms could mainly act as subcontractors employed by large companies (Sforzi, 2002). On the contrary, drawing upon the experience of the economic development of Tuscany and delving into Marshall's theoretical thought, Becattini developed a distinct interpretation of Industrial Districts (Becattini, 1969, 1975a,b). In this interpretation, small producers - specialized in one or a few phases of the same production process- could achieve the advantages of the division of labor - embedded in a local community where social forces cooperate with economic ones [2].

[2] This thesis became extremely popular in Italy after the book "Market and Local Forces: The Industrial District" (Becattini, 1987), influencing Italian legislation in favor of small businesses. The idea of "small is beautiful" has not been unique to Italy. Scholars like Charles Sabel and Jonathan Zeitlin argue that districts of small and medium-sized enterprises offer an alternative to the classical theory of mass production, which, they argue, fails to explain the remarkable persistence of small firms. After an overview of the history of industrial districts, they point to their technological/innovative vitality and flexible production capabilities. (Sabel

Other scholars also refined the concept of Marshallian spillovers in different manners. Glaeser and colleagues synthesized and formalized Marshall's insights by linking them with Arrow and Romer's connections between knowledge and technical progress, culminating in the so-called Marshall–Arrow–Romer (MAR) model (Glaeser, 1994; Glaeser, Kallal, Scheinkman, & Shleifer, 1992). The MAR model posits that knowledge spillovers occur primarily within an industry or between technologically akin ones. A corollary of this model, as analyzed by Glaeser, suggests that local monopolies/oligopolies are more conducive to growth than local competition, as they restrict idea flow and enable innovators to internalize externalities (Glaeser, Kallal, Scheinkman, & Shleifer, 1992).

In contrast, Porter offered an alternative interpretation of Marshallian externalities. While he concurred that knowledge externalities come from specialized and geographically concentrated sectors, he emphasized that local competition –rather than monopoly– catalyzes research and rapid innovation adoption. Despite reducing initial innovator returns, Porter contended that competition compels firms to innovate continuously to outpace their competitors. In a monopolistic setting, dominant firms might prioritize immediate gains over innovation (Porter, 1989).

Of course, both Marshallian and Jacobian spillover theories have implications for the degrees of industrial agglomeration and for company growth rates in specific locations. To synthesize these theories Table 1 provides an overview of the sources of spillover emphasized by the different theories:

Sources of spillovers	**MAR**	**Jacobs**	**Porter**
Specialization	+	-	+
Diversity	-	+	-
Competition	-	+	+

Table 1: Summary of spillover effects.

Indeed the study of externalities regained prominence in spatial-economic analysis when, in the late 1990s, Evolutionary Economic Geography (EEG) emerged as a counter-narrative to the equilibrium-focused propositions of the 'New Economic Geography' (Boschma & Frenken, 2006). In its early stage, EEG research heavily leaned on biological metaphors —- like mutation, adaptation, selection, retention, and variety. A foundational aspect of EEG is its

& Zeitlin, 1985). The necessity of mass production for economic progress is also challenged in Piore & Sabel (1984). They emphasize a craft alternative to mass production, which the authors claim to have been equally susceptible to technological innovation but in the form of general-purpose machine tools capable of small-batch, flexible production.

Under mass production, sub-divided labor and dedicated equipment can reduce unit costs through economies of scale and facilitate new investments in special-purpose technologies, further reducing costs. Conversely, within the realm of flexible specialization, multifaceted labor, and general purpose equipment it is argued that contribute to a decrease in customization expenses through economies of scope, 'broadening' the market for distinct products and fostering investments in adaptable technologies, which in turn diminish the additional cost associated with tailored products and further expand the market (Hirst & Zeitlin, 1991).

micro-level orientation, often rooted in the capability-based theory of the firm. Spatial factors and institutional structures can influence the procedures underlying such organizational capabilities. The ensuing dynamics result in various spatial manifestations -from clusters and agglomerations to networks and core-periphery structures. A cornerstone of EEG is its endeavor to unravel the origins of these spatial economic patterns –which arise from the intricate interplay of individual and collective behaviors– and to comprehend the path- and place-dependent nature of these transformative processes (Boschma & Frenken, 2006). Therefore, a quintessential question for EEG concerns the patterns of the spatial concentration of industries.

EEG scholars posit that clusters arise from local self-reinforcing spin-off processes, where some firms often diversify or branch out from related local industries, but also from the effect of intra or inter-industrial externalities. Evolutionary Economic Geographers argue that the geographical localization of knowledge spillovers is intrinsically tied to the fact that not all knowledge is codifiable but tacit and specific to particular firms and environments. As Winter (2009) suggests, technological knowledge exhibits varying degrees of tacitness. Such tacit knowledge is not easily transferable except through face-to-face interactions and labor mobility, while formal transmission methods are less effective. In this context, knowledge emerges as a sort of localized "public good" shared by co-located economic agents. As a result, knowledge spillovers are geographically confined to the region where new economic knowledge is generated (Beaudry & Schiffauerova, 2009).

In this light, Evolutionary Economic Geography has delved into the theories of knowledge spillovers, rekindling the debate between Marshallian and Jacobian spillovers and examining the advantages of specialization versus diversification for sectoral innovativeness and overall regional performances. Indeed, the central thesis of EEG is that innovation processes heavily rely on locally acquired knowledge, and regional development is fundamentally an endogenous process with strong path dependencies (Castaldi et al., 2015). This implies that the historical and geographical context of a region plays a crucial role in shaping its economic trajectory. Path dependencies suggest that the development trajectory of a region is influenced by its past, with historical events and choices shaping the current economic structure.

Grabher (1993) distinguishes between *adaptation* and *adaptability*. While adaptation pertains to changes following predetermined paths, adaptability concerns the development of new trajectories. In this context, some scholars suggest a trade-off between the two (Boschma, 2017). Regions with greater sectoral specialization, it is suggested, exhibit a pronounced inclination to generate innovations that reproduce existing structures; while they have limited options for new growth paths. On the other hand, diversified locations offer more potential for new recombinations between local activities and are associated with *adaptability*, echoing "Jacobs' externalities". However, overly diversified regions might lack industrial focus –i.e., a critical mass for each industry– and cognitive proximity between local industries.

Frenken et al. (2007) deepen the agglomeration theory by analyzing the effect of related versus unrelated varieties. The authors found that Jacobs's externalities are higher in regions with a related variety of sectors than in regions with unrelated ones. Indeed, in tune with economies of scope at the firm level, knowledge spillovers within the region appear to occur primarily among related sectors, and only to a limited extent among unrelated ones. Castaldi et al. (2017) delve further into this theme by linking the type of variety with innovation types. Indeed, she posits that regions with unrelated industrial varieties are predisposed towards *radical technological innovation* due to opportunities for recombining previously unrelated knowledge domains. Conversely, *incremental innovation* benefits from related variety in a region since it emerges from recombinations of closely related knowledge domains along established paths [3]. These contributions underscore the relationship between agglomeration drivers and sectoral innovation patterns, which we shall extensively discuss below.

More generally, Duranton & Puga (2004) summarise the main themes from the prevailing literature, via three primary categories for the microfoundation of urban agglomeration: centered on sharing, matching, and learning mechanisms. The first two categories may be made consistent with neoclassical mechanisms. The first encompasses benefits derived from sharing indivisible goods, infrastructure, or specialized workforce; the advantages of sharing suppliers, leading to increased sectoral returns; and the impact of sharing the workforce on reducing the covariance between company-specific productivity shocks and wages. The models in the second category illustrate instead the enhanced matching capabilities observed in agglomerated economies. Within these economies, an increase in the local number of agents elevates the expected match quality and reduces frictional unemployment at equilibrium. Lastly, the learning models entail knowledge accumulation, generation, and diffusion. Knowledge accumulation models refer to growth models based on learning by doing and accumulating workers' knowledge in a specific area in their categorization. Knowledge generation models pertain to Jacobsian spillovers, while knowledge diffusion models relate to Marshallian spillovers, based on skill exchanges between workers through face-to-face interactions.

For what concerns the empirical literature, a vast body of studies provides evidence supporting some of these theories, but the results of these studies often diverge (Beaudry & Schiffauerova, 2009). As Frenken et al. (2005) suggest, this "ambiguity in results is probably due, at least in part, to challenges in [...] defi-

[3] Using patent data for US states in the period 1977–99, Castaldi et al. (2015) find support to their hypothesis that regional related-variety is positively associated with regional inventive performance, while regional unrelated-variety is positively associated with the regional ability to produce breakthrough inventions. The link between co-localization of productive units and innovation is the focus Ejermo (2009). In his work, he uses indicators of patent quality to form an index of regional innovation and, by examining the concentration of innovation, reveals that innovations are more concentrated than inventions (proxied by the number of patents), which in turn are more concentrated than production. Moreover, he shows that innovation is concentrated in regions with high production and invention levels. Similarly, the findings of Castaldi & Los (2012) show that the geographical concentration of "superstar" patents among US states is much higher than non-superstar ones. Therefore, companies tend to locate their research for breakthrough innovations in very specific places, while regular innovations are produced in many more locations.

nitions of variety, economic performance, spatial scale, and spatial and sectoral linkages...". Meanwhile, another portion of this ambiguity might be attributed to the level of aggregation of geographical units as Glaeser et al. (1992) note the magnitude of apparent "external effects" increases as the geographical unit becomes smaller.

A few scholars propose the notion that firms are, on average, more productive in larger cities –see Rosenthal & Strange (2003) and Melo et al. (2009) for reviews and summaries of existing findings. A distinct interpretation of to agglomeration economies has been put forth by Melitz (2003) and Melitz & Ottaviano (2008). They interpret this phenomenon by the greater attractiveness of larger markets for firms, which intensifies competition, thereby accounting for the higher productivity in major centers through a sort of "Darwinian selection effect" of firms. However, this alternative explanation is refuted by Combes et al. (2012). The authors integrate the selection model of Melitz & Ottaviano (2008) with a general agglomeration model in the spirit of Fujita & Ogawa (1982) and Lucas & Rossi-Hansberg (2002). On the proof of data on French firms, they try to estimate the relative importance of attractiveness-driven agglomeration versus firm selection across various sectors. Indeed, while selection effects should lead to a more significant left truncation of the firm productivity distribution in larger cities, agglomeration effects should result in a rightward shift of the whole firm productivity distribution, making all firms more productive. Their findings indicate that productivity differences across French metropolitan areas are primarily explained by agglomeration, while another important (and unexplained) result concerns the sectoral heterogeneity of the outcomes.

Beaudry & Schiffauerova (2009) review the findings of 67 articles concerning empirical research on knowledge externalities. They report that approximately 70% of these studies claim to have found evidence of the existence of Marshall externalities and their positive impact on economic growth or innovative output. A comparable proportion of studies (75%) supports Jacobs' thesis of a favorable influence of economic activity diversification in a region. However, they also note that about half of these studies reported at the same time positive and negative or insignificant results depending on the sectors, periods, countries, or dependent variables. Moreover, an exclusively negative influence of agglomeration upon growth is far more often associated with Marshall externalities, suggesting that regional specialization might hinder economic growth since the reduced adaptability of specialized regions can prove critical if the region's main industry is in decline. At the same time, diversification is much less likely to induce this negative effect.

Glaeser et al. (1992) test the predictions of various theories of knowledge spillovers and growth (i.e. Porter, MAR, and Jacobs) using cross-sectional data of 170 city industries in the largest United States cities between 1956 and 1987. They emphasize that these theories are not always mutually exclusive but rather offer different, but possible complementary, views. Their findings show that industries grow faster in places where they are underrepresented and where the medium size is smaller than the national average size of firms in that industry, supporting Jacobs's inter-industries externalities theory and Porter's and Jacob's views that local competition fosters growth. Despite the overall results found by the authors are not favorable to MAR externalities, also because they account for the existence of many cities specialized in a few industries through other externalities, such as sharing inputs, including specialized labor. This study is particularly significant because Glaeser et al. (1992) were the first to suggest that the degree of specialization might be better represented by the use of the "location quotient", and in particular, the following the foundational work of Ellison & Glaeser (1997), acknowledges that any robust measure of localization must 'wash away' a measure of industrial concentration. The approach pioneered by Glaeser and his associates can be elucidated by the "dartboard" metaphor, in which they are able to account for the concentration of firms as deviation from the random agglomeration, which can be seen as a distribution of darts across the board driven solely by stochastic factors (see also below). Among the authors who revisited the index developed by Ellison & Glaeser (1997), albeit with some modifications, are Maurel & Sédillot (1999) who applied it to study agglomeration using data from French industries, and Duranton & Overman (2002), who proposed a modification to the index to work on a continuous measure of location, avoiding the aggregation of information to the level of discrete spatial units, for the analysis of UK data, studied also by Devereux et al. (2004). Bottazzi et al. (2008) refine Ellison & Glaeser (1997) trying to disentangle *sectoral* vs *location* specific agglomeration drivers. A very clear message from all these studies is the strong sector-specific nature of agglomerative tendency, with both Devereux et al. (2004) and Maurel & Sédillot (1999) highlighting that agglomeration seems to be stronger in sectors with low "technological intensity".

Regarding the outcomes of agglomeration, many studies have tried to demonstrate that it is a related variety that primarily supports productivity and employment growth. For instance, Bishop & Gripaios (2010), examining spillovers in 2-digit industries in sub-regions in Great Britain, underscores the presence of a positive effect with substantial sectoral heterogeneity. Similarly, Mameli et al. (2012), examine the impact of sectoral diversity on employment growth in Italy at the level of the Local Labor Systems (LLS) during 1991-2001, and emphasizes the sectoral heterogeneity of the results.

Heterogeneity strongly emerges also in Bottazzi et al. (2002), who emphasizes the coexistence of various agglomeration mechanisms and different empirical agglomeration types, with relevant intersectoral differences. (Our study below bears clear links with that work as well as Bottazzi et al. (2007, 2008); Bottazzi & Gragnolati (2015)).

The foregoing pieces of evidence suggest a general picture characterized by different factors of agglomeration and substantial heterogeneity in the agglomeration drivers, tendencies, and effects across the sectors. The evidence hints at the links between agglomeration drivers and innovation activities. However, no study specifically tries to map the importance and relative weight of the type of agglomeration driver to the patterns of innovative activities themselves. In the work that follows, we aim indeed to bridge this gap in the literature and map the sectoral specificities of agglomeration trends in the corresponding Pavitt classes (Pavitt, 1984, as refined in Dosi 2023), which tries to capture the distinct modes of generation and use of innovative knowledge in the corresponding group of sectors. Relately we shall try to identify the difference balances within location-wide ("urbanization") drivers vs sector-specific forces, conditional to such classes.

4 Data

This research draws upon the "Census of Manufacturers and Services", an extensive dataset maintained by the Italian Statistical Office (ISTAT), which contains data on nearly five million employees and over half a million business units (BUs). Each record specifies the geographical positioning of the employees and business units at distinct time intervals, along with their associated industrial sectors. The geographical units used in these data are called "Sistemi locali del lavoro (SLL)" (local labor systems) and are constructed through the merger of multiple municipalities defined using the daily commuting flows between home and work, so that the boundaries are independent of the administrative structure of the territory but are based on social and economic relationships.
Our investigation primarily centers on the censuses of 2001, 2011, and 2019 (that is the last available revelation), which provide data segmented according to the 3-digit Italian ATECO classification, consistent with the NACE classification framework. In the 2001 census, business units and workforce distribution span 683 geographical entities. In 2019, the local entities remained the same as in 2011, except for two that merged into one due to administrative changes. Thus, in 2011 there were 611 Local labour systems (SLL), and 610 in 2019. Moreover, the data for each manufacturing sector are grouped into Pavitt's technological taxonomies, as updated by Dosi (2023) and showed in table 2, trying to classify specific technological learning regimes, each corresponding to a distinct set of technological paradigms with their specific learning modalities and equally specific sources of technological knowledge. In addition, we separately examine also the service sectors.

In particular, Pavitt's taxonomy includes the following groups of sectors:
(i) Supplier dominated, where innovative opportunities primarily arise from the acquisition of new machinery and intermediate inputs (textile, clothing, metallic products belong to this category);
(ii) Specialized suppliers, including manufacturers of industrial machinery and equipment; this sector is characterized by relatively high internal R&D, a high level of technological opportunity, cumulativeness, and high importance of tacit knowledge. *(iii) Scale-intensive sectors*, where the sheer scale of production influences the ability to exploit innovative opportunities, partly generated endogenously and partly stemming from science-based inputs. These, in turn, are divided into:
iii.1 Scale intensive Continuous, where internal economies of scale are strictly scale-related, and technological opportunities primarily depend on specialized suppliers. The category includes sectors such as Steel, other metals, cement, glass, and refining.
iii.2 Scale intensive Discontinuous, where products tend to be more complex and

internally generated technological knowledge plays a more significant role. The category includes sectors such as Transport equipment, and brown and white goods.
(iv) Science-based industries, whose innovative opportunities coevolve, especially in the early stage of their life cycles, with developments in pure and applied sciences (microelectronics, informatics, drugs, and bioengineering are good examples).
The features of each class are outlined in the table 2, from Dosi (2023).

Taxa	**Typical sectors**	— Sources and procedures of innovation			**Technological Trajectories**
		Tech. opportunities	**Sources of knowledge**	**Cumulativeness**	**Means of appropriation**
Supplier Dominated	Textile, clothing, simple metal products, agriculture	Depend on product innovation in specialized suppliers; generally low	Producers of capital and intermediate inputs	Low	Nontechnical (e.g., trademarks, marketing, advertising, aesthetic design), when applicable. Generally very low
Scale Intensive – Continuous process	Steel, other metals, cement, glass, refining	Largely depend on specialized suppliers	Producers of plants, learning by doing	Low, but high economies of scale	Process secrecy and know-how
Scale Intensive – Discontinuous process	Transport equipment, brown and white goods (TVs, washing machines, etc.)	Medium	Internal R&D, product design, specialized suppliers	Relatively high; economies of scale	Product complexity, learning economies, economies of scale
Specialized Suppliers	Machine tools, industrial machinery, measurement and control instruments	High	Internal R&D, learning by interacting with users, science-based industries	High; tacit knowledge	Technical lags, patents, dynamic learning economies, design know-how, knowledge of users, patents, tacit knowledge, product performances
Science Based	Pharmaceutical, fine chemicals, semiconductors and computers, nanotech	Very high	Scientific advances, internal R&D	High	R&D know-how, patents, process secrecy and know-how, dynamic learning economies

Table 2: Technology-based sectoral taxonomy

Let us start with some basic descriptive statistics. In Table 3, we can observe the trend in the number of employees per Pavitt class over the years, and that for productive units in Table 4. Further, the right-hand part of the tables shows the skewness in the respective distributions.

Over the new millennium, we notice a generalized decline in employees and business units between 2001 and 2011 for all sectors except for services. Furthermore, this decline appears to be particularly drastic for the productive units of more 'technology-intensive sectors', such as Science-Based, Scale-Intensive Discontinuous, and Specialized Suppliers. This decline is much more pronounced for productive units than for employees in almost all sectors, except for specialized suppliers. This pattern is confirmed by the dynamics in the firm sizes in various sectors reported in Table 5. With the remarkable exception of the "Specialized Suppliers" category, and to a lesser extent, "Continuous Process Scale-Intensive", the decline in employment and employees continues between 2011 and 2019, with a consistently greater reduction in productive units than in employees.

Basically, the data vividly highlight a long-term pattern of Italian deindustrialization. In all that, first, notice that we are talking about strikingly low mean sizes. In other words, the Italian "dwarfism" is a persistent phenomenon. Second, inter-firms heterogeneity at least in terms of size does not decrease.

The distribution of the forgoing variables shows a skewness that is always positive and does not decrease for any sector in any year. Rather, it increases, particularly for specialized suppliers, scale-intensive, and science-based sectors. This suggests the possibility of a reallocation of employees within the surviving firms, such that relatively smaller firms appear to have experienced a more significant downsizing of employment compared to larger ones. This observation aligns with the discussion of the neo-dualism of Italian industrial structure in Dosi et al. (2021): heterogeneity across firms has increased in the new millennium, especially after the 2008 crisis, which in turn contradicts the common belief in the healthy cleansing role of recessions.

	Employees			Skewness		
CLASS	2001	var2011	var2019	n2001	n2011	n2019
S_B	251432	-0.19	-0.05	0.64	0.83	0.79
SD	2489609	-0.18	-0.05	0.03	0.04	0.05
Serv	14241399	0.12	-0.14	0.01	0.01	0.01
SI_C	684143	-0.17	-0.08	0.14	0.18	0.20
SI_D	474798	-0.12	-0.02	0.24	0.31	0.28
SS	1152577	-0.43	0.04	0.08	0.13	0.13
TOT	19293958	0.028	-0.128	-	-	-

Table 3: Employess and skewness

	Productive Unite			Skewness		
CLASS	2001	var2011	var2019	n2001	n2011	n2019
S_B	19689	-0.51	-0.11	0.58	0.77	0.84
SD	415203	-0.20	-0.12	0.04	0.04	0.05
Serv	4076206	0.15	-0.08	0.01	0.01	0.01
SI_C	53436	-0.31	-0.15	0.15	0.20	0.23
SI_D	36300	-0.56	-0.08	0.25	0.29	0.30
SS	126695	-0.42	-0.06	0.09	0.17	0.18
TOT	4727529	0.092	-0.087	-	-	-

Table 4: Productive Unite and Skewness

Class	2001	Δ2011	Δ2019
Serv	7.98	0.41	-0.47
SS	27.73	-0.53	-0.02
S_B	16.93	0.76	0.16
SI_D	52.81	0.12	0.21
SI_C	34.77	-0.27	-0.2
SD	9.19	-0.22	0

Table 5: Mean Employees

All these analyses are conducted by mapping them onto Pavitt's classes, where enterprises are divided into.

5 The Models:

In order to understand more rigorously the observed patterns, let us try to characterize the apparent stochastic process leading to them.

It is useful to refer to the 'dartboard' metaphor from Ellison & Glaeser (1997), upon which one builds also in Bottazzi et al. (2008) and Bottazzi & Gragnolati (2015). Imagine each location in space to be a dartboard to which darts (firms or plants) of different colors (sectors) and different sizes (e.g. in terms of employment) are thrown. Darts of any type may be thrown blindly, leading to a homogeneous random space. Deviation from pure randomness may be driven by two factors.

First, particular locations may be attractive (or repulsive) in their own right, irrespectively of the color (i.e. sector/technology) of the dart. These are generic cross-sectoral ("urbanization") location-specific drivers.

Conversely, second, there might be sector-specific drivers that hold orthogonally across locations. Given all that, there are tricky analytical issues. First, as mentioned, there might be 'darts' of different sizes. They could be relatively few but quite big ones. So, one ought to differentiate between, say, an Italian textile 'district' made of many relatively small firms vs. e.g. agglomerations with few big automobile firms and a long tail of smaller suppliers.

Second, relatedly, one might find clusters of industries interlinked via input-output relations and/or inter-sectoral knowledge-based flows.

Third, more fundamentally how does one characterize the process of location over time? Putting in another way, granted the two foregoing agglomeration drivers, to what degrees does history count?

At one extreme suppose that increasing returns (no matter whether location-wide or sector-specific) are set in motion by the actual process of location so that the 'attractiveness' of any one place depends on the actual (stochastic) history of locations there. More formally, one may represent it with Generalized Polya Urns, that is time-dependent infinite-states Markov Chains, possibly handling both increasing and decreasing returns along endless location paths (Arthur, 1990a,b; Dosi et al., 1994; Dosi & Kaniovski, 1994). Under this setup, history counts a lot, possibly even too much, in the sense that the past progressively 'solidifies' into increasingly rigid patterns of relative attractiveness across location/sector, while small initial events are amplified via some increasing returns dynamics (for a discussion see Castaldi & Dosi, 2006). So, to caricature, the 'Silicon Valley' would not have existed without Shockley -the inventor of the transistor- having a girlfriend in San Francisco, or New York would not have been New York, without a few Dutch Calvinists founding a little colony named 'New Amsterdam'. Whether the formal representation is empirically adequate or not, in order to bring it to the actual evidence one needs a long time series with actual entries and exit per period (The only attempt to our knowledge is Dosi et al., 2019). However, these data are extremely hard to find and one is bound to confine the analyses to essentially cross-sectional data (or, at best, a quite short series).
At the opposite formal extreme, one may assume finite numbers of locations and 'investors' with totally reversible 'choices'. Further, add the idea that each 'period' is an equilibrium (indeed a notion we find quite unpalatable). Then the setup boils down to a finite-state Markov process wherein each observation is the limit distribution of a 'process' that occurs within the period itself. The reader should be fully aware that under such a setup history basically does not count at all except within the period (say the 'year'). However, this is what we shall study, reluctantly, in the following, as one we did with similar data in Bottazzi et al. (2008) and Bottazzi & Gragnolati (2015). Firms, regardless of locations and sectors, die, and are exactly replaced by a new firm. Each firm, in each period, is located, in probability, according to the perceived benefit of the location, conditional on its 'attractiveness ', together with a technology/sector-specific preferential attachment. There are L locations and I sectors, each characterized by a variable number of firms for a total of N entities.

5.1 Some specifications

It might be useful to begin with the null model as a benchmark, where the space is 'completely flat' and location patterns are perfectly random:

1. **Null model:**
   In this model all locations possess uniform geographic attractiveness a with

no agglomeration parameter b over any sector,

$$a_l = 1/L$$

Therefore in this case the marginal distribution of the number of firms in a location (l) in this case depends uniquely on the total number of firms in the sector and the number of locations:

$$\Pi(n; a, b, N, L) = \frac{N_j}{L} \tag{5.1}$$

This model is the simplest one that can be used to answer the question: does some form of agglomeration exist? Any deviation from this null model measures a level of agglomeration different from that given by a random placement on the map. Granted that, of course, a quite different matter concerns the nature of such deviation from sheer randomness.

2. **Ellison and Gleaser model:**
In this respect, an important benchmark is Ellison & Glaeser (1997) concentration index, nowadays one of the most widely used in the literature. The index is constructed to capture the difference between the observed agglomeration and the pattern that could have been observed if all sectors were (in probability) aligned with each other according to the overall size of each location. In particular, call $s_1, s_2, \ldots, s_M$ the share of employment in a given industry in all locations i, and the share of aggregate employment in the same locations $x_1, x_2, \ldots, x_M$. By subtracting the two one obtains a measure of departures of the sectors/locations from the overall distribution.

$$g = \sum_i (s_i - x_i)^2 \tag{5.2}$$

The normalized measure is given by:

$$G = \frac{\sum_i (s_i - x_i)^2}{1 - \sum_i x_i^2} \tag{5.3}$$

The fundamental property of this measure is that in the absence of spillovers or any other advantages specific to an industry, the expected value of G is equal to the Herfindahl-Hirschman index, measured with the size of the plants in terms of employees. Further, deviations resulting from the presence of spillovers or natural advantages of the spatial entities yield a deviation from $E(G)$ relative to H, captured by γ:

$$E(G) = \gamma + (1 - \gamma)H \tag{5.4}$$

Rearranging eq. 5.4, one can compute γ as:

$$\gamma = \frac{G - H}{1 - H} = \frac{\sum_i (s_i - x_i)^2 - (1 - \sum_i x_i^2) \sum_j z_j^2}{(1 - \sum_i x_i^2)(1 - \sum_i z_j^2)} \tag{5.5}$$

Agglomerative tendencies are computed as a deviation from the agglomeration that could have been found if firms (of diverse sizes) had chosen locations for their plants by randomly selecting areas on the maps just as a function of the overall economic 'size' of the area itself. In particular, this index "cleans" out the plant-size effect in the study of agglomerations phenomena. Moreover, another critical property of the models is that it defines as its own "null model" a random concentration as probabilistically driven by the share of firms of all sectors in the same location, thus "cleaning out" also urbanization-related agglomeration drivers. The downside of the index is that it cannot properly represent intersectoral agglomerative forces but rather just the deviations from a uniform urbanization pattern. To illustrate think of a perfectly random sector, with only one firm in each region: still, it shows a deviation from what the EG null model would predict, showing a positive γ, even though there is no actual geographical concentration (see the example in the Table A.2 in the appendix).

3. **Heterogeneous location with null agglomeration economies:**
A significantly different model with a different measurement of agglomeration patterns draws from Bottazzi & Secchi (2011), and investigates a repeated choice model under linear externalities: see Bottazzi et al. (2007). The model conceptualizes the observed distribution of firms in different locations as the results of a Markov process which entails perfect reversibility in firms' locational decisions, leading to invariant limit distribution which are supposed to characterize each 'period' of observation. Specifically, firms established in a location have an inherent probability of terminating their operations in each period. Concurrently, new firms, finite in numbers but chosen from an infinite pool of potential entrants, enter into the system, selecting their production sites based on anticipated benefits.
The location drivers are divided into a 'constant' and a 'social' element. The first is called *location-specific* driver, which includes location-wide externalities that compose the attractiveness of a location and lead to a horizontal pull across different economic activities, and it may be linked to the literature on urbanization and to *Jacobian spillovers*.
The second driver is instead *technology-specific*. It arises from sectoral and technological organization specificities within each sector or groups of sectors, and it is related to localized forms of knowledge accumulation. The *technology-specific* component represents the strength of *sectoral localization economy* and plausibly includes also what are often called *Marshallian spillovers*.
In line with Bottazzi & Secchi (2011) we begin by exploring a model whereby the probability that a *new entrants* from sector 'j' chooses location 'l' according to a probability:

$$p_{j,l} \sim a_{j,l} + b_j n_{j,l,t-1} \tag{5.6}$$

Here, 'a' stands for the inherent "geographic attractiveness" (the *urbanization economies*) of each location, while 'b' –contingent on the number of

firms in the same sector which have already entered– captures the potency of the *localization economies* $n_{j,l}$. Note that here time suffix t just stands for the unfolding of a notional process of the within-period sequence, us limit is the actual observation of that period.
Given the property of ergodicity of this model the probability of finding n out of N firms in a location characterized by coefficients (a, b), $\Pi(n; a, b, N, L)$, can be easily obtained from the limit distribution $\Pi(n; a, b)$ (Bottazzi & Secchi, 2011). Considering each observed distribution of firms as the limit distribution of a process of *repeated choice under (within the period) dynamic externalities*, the parameters a and b can be estimated via Maximum Likelihood method.
In this scenario, the equilibrium distribution is a function of both a_l and b_j.
In the specific case of null sector-specific externalities (that is $b = 0$), the equilibrium distribution of firms across locations, $n = (n_1, \ldots, n_L)$, takes the multinomial form:

$$\Pi(n; a, b = 0) = \frac{N!}{\prod_{l=1}^{L} n_l!} \prod_{l=1}^{L} a_l^{n_l} \tag{5.7}$$

In this model the distribution of firms observed in each location l would depend on a_l/A, the number of firms and locations.

4. **Heterogeneous location with agglomeration economies:**
Last, let us relax both the homogeneity assumption among locations, allowing for distinct geographic attractiveness a_l for each location l and the (sector-specific) agglomeration economy b, holding across all locations. In this scenario, the marginal distribution of the number of firms in a location with geographic attractiveness a adheres to a Polya distribution:

$$\Pi(n; a, A, b, N, L) = \binom{N}{n} \frac{\Gamma\left(\frac{A}{b}\right)^n}{\Gamma\left(\frac{A}{b} + N\right)^n} \frac{\Gamma\left(\frac{a}{b} + n\right)^n}{\Gamma\left(\frac{a}{b}\right)^n} \frac{\Gamma\left(\frac{A-a}{b} + N - n\right)^n}{\Gamma\left(\frac{A-a}{b}\right)^n} \tag{5.8}$$

Here, $A = \sum_{h=1}^{L} a_h$. The marginal distribution, for a location with attractiveness parameter $a_l = a$, is influenced by the total number of firms N, the aggregate number of locations L, the parameter b, and the location-specific parameters a_l through their cumulative value A.

In order to proceed to the empirical investigation, however, notice two things. First, given the cross-sectional structure of the data, it is not possible to estimate a specific parameter for each location. Therefore, the assumption that we make is that the "attractiveness" of the location is positively correlated with the number of firms in all sectors already present in it, as:

$$c = exp(a_1 * log(n_l) + a_0) \tag{5.9}$$

Second, a_l and b always appear in the current specification of the model as a ratio, making it difficult to estimate their separate impact. Therefore, a generic functional specification of the model can be obtained by setting:

$$\frac{a_l}{b} = c(\theta, x_l) \tag{5.10}$$

Notice also that the last two models differ from the EG in two crucial respects. First of all the latter unfortunately does not wash out the plant-concentration effect from the computation of agglomeration index. One way of interpreting it is by considering plant concentration as an indicator of the internalization within a single firm plant of potential externalities, and thus a kind as an extreme agglomerative force.

Second, the latter models do not see agglomeration as a deviation from a pure urbanization force but are more expansive in their notion of agglomeration itself and account also for those "general" agglomeration forces which are the "null model" of EG.

However, since in the latter model the deviations from the null one can represent whatever form of agglomeration (both urbanization and sector-specific), we need to find some methods to compare the strength of the two drivers. An admittedly approximate one entails the use of Akaike Information Criteria (AIC) to compare the accuracy of location vs sector-specific drivers.

In fact, the Akaike Information Criterion (AIC) serves as an estimator for prediction errors and, consequently, evaluates the relative quality of different statistical models. When confronted with a range of models for the data, AIC assesses how well each model performs in comparison to the others, providing a basis for model selection [4].

Consider a statistical model based on whatever data, where k is the number of estimated parameters in the model and $\hat{L}$ is the maximized value of the likelihood function for the model, the AIC value for the model can be expressed as:

$$\mathrm{AIC} = 2k - 2\ln(\hat{L}) + \frac{2k(k+1)}{n-k-1} \tag{5.11}$$

When presented with a set of potential models for the data, the preferred model is the one with the minimum AIC value.

We use the Akaike Information Criterion (AIC) to compare the Multinomial model, as from eq. 5.7 and the Polya model, as from eq. 5.8 i.e., in order to determine which model better fits our data. We analyze the difference between AIC Polya and AIC Multi for each period. This allows us to assess whether intra-sectoral or inter-sectoral agglomeration drivers appear to be relatively more important and, with that also the variance in this importance across Pavitt's classes.

[4] AIC is rooted in information theory. Since a statistical model used to represent the data-generating process is rarely exact, there is always some loss of information incurred by using any model. AIC quantifies the relative amount of information lost by a specific model, favoring models that retain more information.
To estimate the information lost by a model, AIC balances the trade-off between the model's goodness of fit and its simplicity.

6 Empirical analysis

6.1 Null model 1

Let us start with our own null model. Specifically, 200 distributions of firms are simulated for each sector following the distribution outlined by Equation 5.1. Subsequently, the parameters are estimated according to the model from 5.8. Thus we test the existence of agglomeration forces when compared to the possibility of a random distribution with purely random agglomeration observations, using the simulations as a null model.
The results, shown in Table A.1 in the appendix, indicate that the coefficients for each sector in each period are significant (complete tables are shown in the appendix), both when location is measured in terms of the number of firms and of employment. This might appear a trivial and intuitive result. In fact, it is not at all. Apparent heterogeneity across relatively small geographical entities might well be the outcome of pure randomness. Our results confidently show that they are not and thus the economic space is far from "flat" and uniform. Spatial heterogeneity is a ubiquitous property. However, what determines it remains a challenging object of investigation.

For sure there are three possibly inter-related major candidates.
One just concerns various forms of increasing returns internalized between single firms/plants so that observation of apparently heterogeneous space has just due to their discrete location. Think for example of an extreme of a single plant/firm monopolizing all the production in a certain activity located in a single location. This would lead statistically to a spatial heterogeneity that has little to do with "agglomeration", unless that is understood in a very expansive way, covering also increasing return of any kind.
A second ensemble of drivers of agglomeration concerns more strictly the advantages of *urbanization* due to pecuniary externalities, ranging from transportation costs, easy availability of all types of inputs, etc.
A third, often mixed in the literature with the forgoing ones, concerns the *sector specific* forms of knowledge generation and diffusion and their spatial locations. Their identification is the central task of this work taxonomizing the sources and methods of knowledge generation, transmission, and appropriation of knowledge, and mapping them into the revealed pattern of spatial agglomeration.

6.2 The Ellison and Gleaser model

A solid point of departure is the estimate of the model of Ellison & Glaeser (1997) (EG) spelled out above.
Their seminal attempt in this model is to separate sheer urbanization-related drivers from sector-specific ones and it does so by "washing out", so to speak, also the apparent agglomeration due to the internalization of increasing returns, (c.f. above), via economies of scale, etc, within a few plants and firms. They do that by substrating the sectoral concentration indices from their agglomeration

estimates.
Unfortunately, in our estimates, we lack any information on the distribution of the size of the plants as we have only the number of employees and business units per location, thus preventing a proper estimation of a Herfindahl-Hirschman Index (HHI). Therefore, for each location/sector, we can only use the number of firms and their average size. Thus, the actual Herfindahl-Hirschman Index (HHI) can be only approximated on the grounds of these data, with two major drawbacks. First, the "true" HHI is likely to be heavily underestimated, consequently causing our Gamma values to be generally higher than those estimated by EG. Second, the results might also be biased across sectors, resulting in particularly lower estimates for sectors where the size of the plants is more heterogeneous compared to those where plants/companies are more homogeneous in size.

With these caveats in mind, looking at the results presented in table 6, the values of G are nevertheless interesting and challenging. For example, the Supplier Dominated sectors, traditionally more geographically agglomerated, tend to display rather low G and Gamma values, compared to e.g. SB and Scale Intensive sectors which, in Italy, generally do not show a specific agglomerative tendency.

The evidence, however, in our imperfect estimates, is unable to distinguish (i) general urbanization-wide externalities, from (ii) sectoral economies of scale internalized within single firms/plants (what EG does, and we cannot do), and, (iii) "genuine" sector-specific agglomeration forces. Thus, G in SI and SB sectors could be higher because these sectors typically have larger companies, and their HHI might be particularly underestimated, making it difficult to cleanse the size effect from the agglomeration index in the Gamma calculation. Indeed, the EG index cannot well distinguish between inter-sectoral differences in agglomerative forces and "anti-urbanization" tendencies. In fact, sectors that do not have an "intrinsic" tendency but are "repelled" by urban centers appear "agglomerated" since the assumed null model distribution implies that the probability of a company entering a location is correlated with the share of all other companies present there, which in turn might or might not reveal any underlying agglomerative driver.

To illustrate this potential problem, we conducted a simulation with two sectors. The first is perfectly distributed with a single company in each of the 10 locations, and the second has one company in each location where there are fewer than 15,000 employees. Both sectors have zero intra-sectoral agglomerative tendencies, but a repulsive drive from urbanized centers also characterizes the second. The results are presented in Table A.2 in the appendix. As one can see, the model assigns a positive agglomerative force to both, which is greater in the second sector (identified as anti-urb), as it has larger deviations from the "null" distribution.

	with metropolies											
	2001				2011				2019			
CLASS	Gamma	G	HH	GG	Gamma	G	HH	GG	Gamma	G	HH	GG
S_B	0,0350	0,0366	0,0017	0,9564	0,0485	0,0509	0,0026	0,9499	0,0325	0,0361	0,0038	0,9125
SD	0,0214	0,0219	0,0005	0,9792	0,0174	0,0177	0,0004	0,9818	0,0215	0,0223	0,0009	0,9795
Serv	0,0063	0,0065	0,0001	0,9782	0,0077	0,0079	0,0007	0,9636	0,0101	0,0104	0,0003	0,9765
SI_C	0,0740	0,0938	0,0219	0,8186	0,0378	0,0666	0,0295	0,6967	0,0547	0,0601	0,0059	0,9219
SI_D	0,0288	0,0320	0,0035	0,9413	0,0585	0,0650	0,0069	0,9261	0,0451	0,0534	0,0089	0,9054
SS	0,0178	0,0195	0,0018	0,9586	0,0106	0,0109	0,0004	0,9721	0,0110	0,0114	0,0003	0,9736
	without metropolises											
	2001				2011				2019			
CLASS	Gamma	G	HH	GG	Gamma	G	HH	GG	Gamma	G	HH	GG
S_B	0,0207	0,0247	0,0041	0,8497	0,0326	0,0398	0,0076	81.36	0,0103	0,0108	0,0005	0,9383
SD	0,0185	0,0192	0,0007	0,9548	0,0163	0,0169	0,0006	0,9525	0,0184	0,0185	0,0001	0,9832
Serv	0,0012	0,0014	0,0002	0,9254	0,0014	0,0017	0,0003	0,8962	0,0011	0,0011	0.00	0,9670
SI_C	0,0763	0,0857	0,0098	0,8443	0,0641	0,0690	0,0051	0,8800	0,0294	0,0296	0,0002	0,9813
SI_D	0,0195	0,0260	0,0067	0,8674	0,0370	0,0511	0,0150	0,8224	0,0150	0,0156	0,0006	0,9648
SS	0,0129	0,0161	0,0033	0,9090	0,0101	0,0107	0,0007	0,9446	0,0060	0,0061	0.00	0,9833

Table 6: EG results

CLASS	G 2001	G 2011	G 2019
S_B	0,0142	0,0219	0,0169
SD	0,0222	0,0165	0,0189
Serv	0,0039	0,0043	0,0047
SI_C	0,0371	0,0158	0,0162
SI_D	0,0129	0,0211	0,0234
SS	0,0088	0,0080	0,0074

Table 7: EG on Business unit

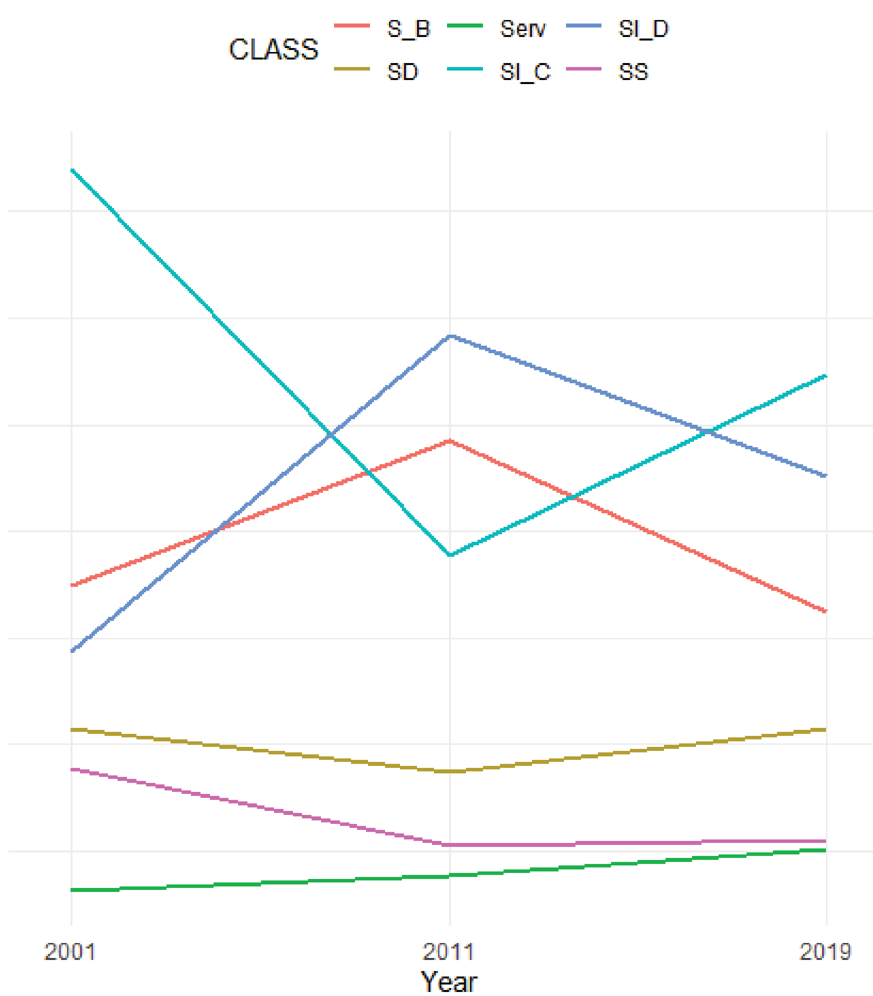
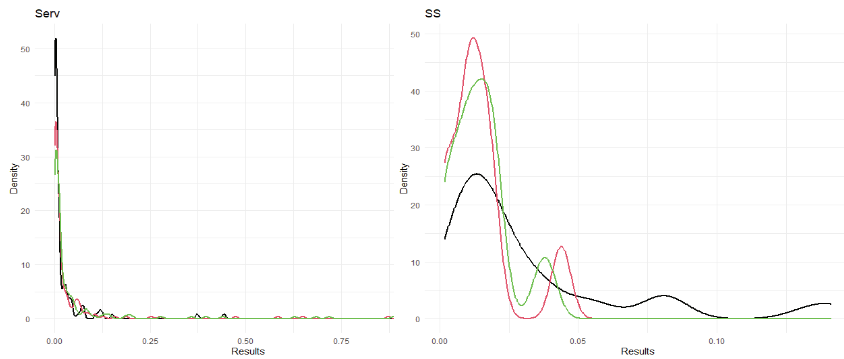
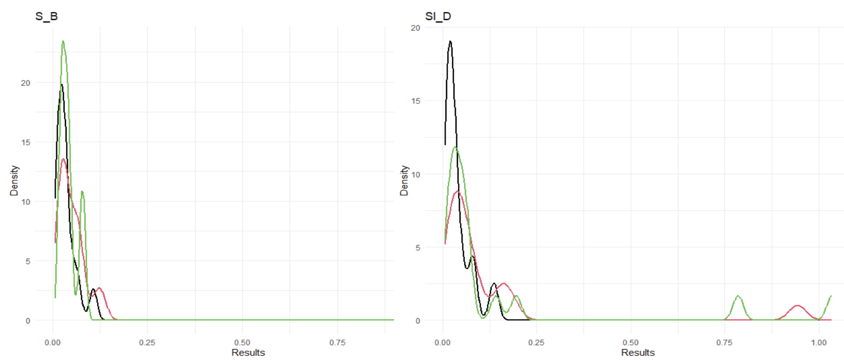


Figure 1: G for each Pavitt class

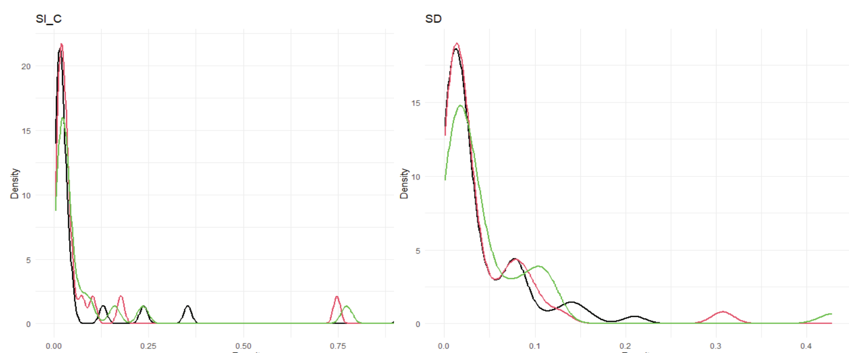
Finally, figure 1 shows the trend of the G index over the years for each Pavitt class, while figure 2 shows the distribution of the latter among the sectors belonging to each class for each year. In particular, we can observe its strong instability, especially in the discontinuous SI, continuous SI, and Science-Based sectors. This instability is also reflected in figure 3 regarding the parameter estimated by the Polya model (c.f. Eq. 5.8). In other sectors, however, we can observe a decline in the G index in 2011 followed by a subsequent increase in 2019, which is also consistent with subsequent results.



(a) Services (b) Specialized Supplier



(c) Science Based (d) Scale Intensive Discontinuous



(e) Scale Intensive Continuous (f) Supplier Dominated

Figure 2: Sectors distribution of estimate G for each Pavitt class.
Red line for 2001, green for 2011, blue for 2019.

6.3 Heterogeneous location with agglomeration economies:

In tables 8 and 9 , we can observe the trend of the parameter $\frac{b}{b}$ over the years and across different sectors, conducted on all available locations, the three middle columns report the results of analyses excluding metropolitan areas, and excluding locations that ISTAT reports as "district" areas (on the details of the definition see Appendix A.6). Table 8 is calculated based on the number of employees per location, while Table 9 is based on the number of Business Units.
We can immediately notice the heterogeneity of the parameters ratio across classes, which is a circumstantial evidence of the influence of diverse innovative patterns on the relative strength of agglomeration drivers.
At one extreme, we can observe that for Science-Based industries, the relative importance of intra-sectoral agglomeration economies is lowest. This is in line with the knowledge sources of this class, which are more based on scientific advances and internal R&D than on learning by doing or other forms of "locally distributed" knowledge. And, admittedly, we do not have in Italy anything looking like Silicon Valley or Route 128 in the USA. For other reasons, the services sector ranks low in terms of the relative importance of agglomeration economies, as "urbanization" can be accepted to be the main location driver.
At the other extreme, the class with the highest ratio covers the Supplier Dominated sectors. Indeed, this class includes more traditional sectors, where innovation largely comes through the introduction of new inputs or machinery and 'local', 'informal' knowledge is likely to matter. Given the low relevance of the internal R&D and engineering capabilities, their competitive advantage is based less on sheer innovative activities and more on professional skills, tacit type of knowledge, and local spillovers.
Another interesting finding is the difference between Scale-Intensive *Discontinuous* Process and Scale-Intensive *Continuous* Process sectors. Somewhat puzzlingly one observes from both Tables 8 and 9 that SI_C appears more inclined towards intra-sectoral agglomeration. It is true that these sectors, like SD one, depend less on R&D and more on inputs from specialized suppliers, and the accumulation of knowledge is predominantly based on learning by doing, which coincides with a more tacit type of knowledge. However, the estimate might just be a spurious effect of sheer concentration. Indeed, it is interesting to note the difference between the parameters shown in Table 8 compared to Table 9, showing that intra-sectoral agglomeration is stronger when calculated in terms of the number of employees rather than the number of firms. This is in line with the fact that both are "Scale-Intensive" sectors, usually with large companies that aim to internalize knowledge spillovers as much as possible.
These differences between classes are stable across various specifications (with or without metropolitan areas or districts), highlighting the robustness of the results.

	with metropolis			without metropolies			without districts		
class	2001	2011	2019	2001	2011	2019	2001	2011	2019
Serv	1.05	1.05	1.07	1.14	1.13	1.17	1.06	1.05	1.07
SS	1.22	1.15	1.19	1.11	0.96	1.00	1.14	1.13	1.18
S_B	0.98	0.96	1.00	1.01	0.91	0.96	0.98	0.95	1.00
SI_D	1.23	1.17	1.20	1.13	0.98	1.08	1.15	1.15	1.18
SI_C	1.33	1.28	1.34	1.22	1.12	1.26	1.26	1.27	1.33
SD	1.40	1.40	1.46	1.40	1.37	1.48	1.31	1.34	1.41

Table 8: **Proxy for the parameters $\frac{b}{a_1}$ - Employees**

	with metropolis			without metropolies			without districts		
class	2001	2011	2019	2001	2011	2019	2001	2011	2019
Serv	1.07	1.07	1.07	1.10	1.09	1.06	1.08	1.07	1.07
SS	1.11	1.08	1.12	1.12	1.08	1.09	1.03	1.03	1.08
S_B	0.90	0.85	0.90	0.91	0.85	0.95	0.88	0.82	0.88
SI_D	1.10	1.10	1.13	1.12	1.13	1.21	1.03	1.06	1.08
SI_C	1.22	1.14	1.18	1.25	1.16	1.24	1.14	1.11	1.14
SD	1.29	1.29	1.32	1.33	1.31	1.33	1.21	1.23	1.26

Table 9: **Proxy for the parameters $\frac{b}{a_1}$ - Business Units**

Considering the analyses without metropolitan areas, it is interesting to note that the parameters for SS, SI_D, and SI_C are lower compared to those with all locations when based on employee data, but higher when based on business units. This indicates a tendency for larger enterprises in these sectors to be located in metropolitan areas themselves, while a greater number of smaller enterprises appear to be located across non-urban agglomerations.
Excluding "districts", on the other hand, the parameters are lower compared to the analysis on all locations for all classes, with the obvious exception for services and an interesting one for Science-Based industries: here there are no "districts" but rather (mild) tendencies to locate where there are possibly urban-based sources of knowledge.

Of course, we have undergone an assessment of the significance of our results. Details are presented in Table A.3 of the appendix. For this test, sectors were randomly assigned to different classes while keeping the number of sectors per class constant, consistent with the empirical analysis, repeated one thousand times per year. Subsequently, the mean and variance of the differences between each pair of simulated classes were estimated and used as statistics for the null model to estimate the significance level of the empirically found differences.
In addition, the analysis was repeated considering the population size in the area as a proxy for urbanization instead of the number of all other businesses present in the location. The results obtained are consistent with those estimated using the number of all businesses (c.f. Table A.5).

Analyzing the trend in parameters over the years in Tab. 10 and 11, we can observe a general decrease between 2001 and 2011, with the exception SD and SI_D sectors, followed by a (milder) increase in the following decade.
An exception among the classes is, not surprisingly, the Services category, but also the Supplier Dominated, which is the sole manufacturing class that does not seem to display falling agglomeration forces in these years.

However, the decline in the parameter in the analysis based on employees without metropolises is for almost all sectors relatively greater: extra-urban agglomerations have been particularly affected for all sectors compared to sectoral concentrations in urban areas. This process has been particularly strong for SI_D and Specialized suppliers, which are also the sectors where the decrease in the estimated parameter on BU has been much lower compared to that estimated on employees.

Overall, it seems that the trend of downsizing of personnel has acted more intensively among extra-urbane agglomerated firms, affecting particularly small to medium-sized ones located in the districts. This is in tune with the descriptive statistics of section 4, and matching also the trend in Skewness of size distribution that is increased over the first period of analysis (c.f. Table 3).

	with metropolis		without metropolies		without districts	
class	Δ2011	Δ2019	Δ2011	Δ2019	Δ2011	Δ2019
Serv	0.10	1.89	-1.15	3.95	-0.34	1.51
SS	-5.95	3.93	-13.83	3.88	-1.53	4.92
S_B	-2.22	4.26	-9.71	5.17	-2.61	4.58
SI_D	-4.55	1.85	-13.37	10.63	0.62	1.90
SI_C	-3.32	4.36	-8.05	12.08	0.33	5.24
SD	0.24	3.76	-1.98	7.82	2.35	4.88

Table 10: **Variations $\frac{b}{a_1}$ proxies- Employees**

	with metropolis		without metropolies		without districts	
class	Δ2011	Δ2019	Δ2011	Δ2019	Δ2011	Δ2019
Serv	-0.66	0.19	-0.71	-2.37	-0.96	-0.13
SS	-2.74	4.19	-3.43	0.84	-0.13	4.18
S_B	-6.39	6.77	-6.19	11.64	-7.23	6.91
SI_D	0.26	3.05	0.55	7.50	3.23	2.28
SI_C	-6.93	3.50	-7.32	7.61	-3.24	3.07
SD	-0.25	2.05	-1.81	1.84	1.99	2.56

Table 11: **Variations $\frac{b}{a_1}$ proxies- Business units**

Over the following decade, one observes a partial reverse trend, especially in districts and in extra-urban areas in general. Conversely, contrary to expectations, the increase in agglomeration forces for Supplier-dominated sectors seems stronger once the district areas are excluded. This is obviously puzzling as Supplier-dominated sectors are traditionally more agglomerated in so-called districts. This seems an indication of the fact that the agglomerative strength of Supplier-dominated sectors has moderately spread more evenly beyond the districts themselves.

Concerning differences between years, we conducted a significance test using the difference in means test, obtained by calculating the mean and standard deviation of the parameter among the sectors of the various groups. The results, all significant, are shown in Table A.4 in the appendix.

6.3.1 Akaike information Criterion

Another angle through which we can appreciate the relative importance of location-wide vs sector-specific forces of agglomeration is based upon the Akaike Information Criterion comparing the Multinomial model, (Eq. 5.7), and the AIC of Polya, (eq. 5.8), for each period:

$$\Delta\text{AIC Multi-Polya}_t = \text{AIC Multi}_t - \text{AIC Polya}_t$$

Table 12 and 13 show the result.

	with metropolis			without metropolies		
class	2001	2011	2019	2001	2011	2019
Serv	69560.00	54351.24	50124.24	53869.69	41361.70	26641.59
SS	153078.57	119192.72	125936.98	127036.17	89164.79	58384.44
S_B	68921.20	57514.05	62327.06	53306.22	43579.96	33514.52
SI_D	189545.96	149560.93	137524.51	163031.82	103612.70	63473.72
SI_C	149042.22	94970.31	93873.65	133257.75	74064.40	65975.77
SD	150929.07	123661.86	122538.42	136313.20	104839.83	92991.77

Table 12: Difference between AIC Multi and AIC Polya -Employees

	with metropolis			without metropolies		
class	2001	2011	2019	2001	2011	2019
Serv	9325.02	7082.74	7134.01	7087.41	5266.48	7033.71
SS	8198.68	4188.17	4241.10	7202.83	2881.69	2244.67
S_B	587.96	330.31	330.52	501.39	238.73	330.62
SI_D	8313.91	1178.24	1172.57	8110.63	885.23	1154.93
SI_C	7406.38	1929.15	1982.71	7130.52	1418.71	1608.45
SD	11887.84	10059.24	10391.96	10814.20	8383.68	8122.39

Table 13: Difference between AIC Multi and AIC Polya -Business units

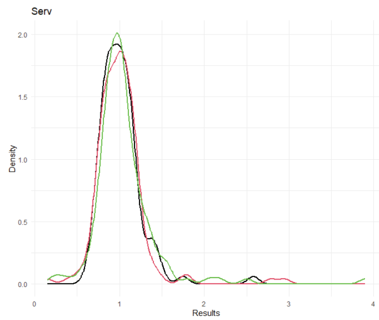
We can immediately notice that the difference between AIC_M-AIC_P is always positive, meaning that the Polya model fits the data better than the Multinomial model, highlighting the cross-sectional importance of intersectoral agglomeration

economies for all classes.
Regarding the consistent heterogeneity detected, the results align with those in Tables 8 and 9, particularly on the lower values for Science-Based sectors, the class with more codifiable knowledge, as mentioned, stemming from external sources such as research centers and universities rather than other firms. Conversely, the differences are higher for supplier-dominated and specialized supplier sectors for the opposite reasons.

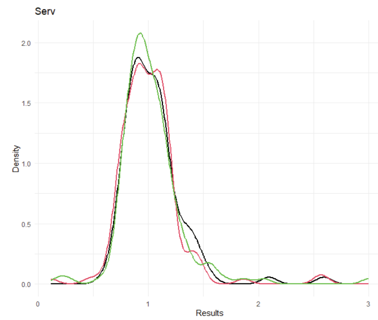
6.3.2 Distributions of parameters

Let's now consider the distribution of the parameter $\frac{b}{a_1}$ over sectors in each Pavitt class over the three years. (Figure 3 displays on the left the results on the distribution based on employees and on the right on business units). If history counts as it should one might observe a relative stability over the years. What is striking is stability in the Services and Supplier Dominated classes, concerning Specialized Supplier one observes agglomerative stability in terms of business units but turbulence in terms of employees. Conversely, there is a high instability of Scales Intensive ones, especially SI continuous, and Science-Based.

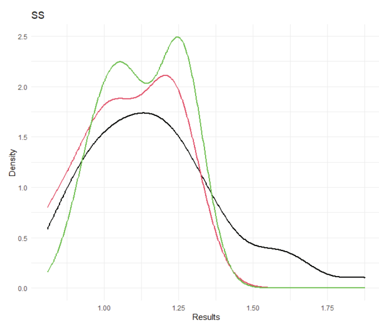
Persistence over time is indeed a crucial condition for the existence of systematic agglomeration (or anti-agglomeration) forces, and this seems to apply only to Supplier Dominated and largely Specialized Supplier categories, and, for opposite reasons, Services.



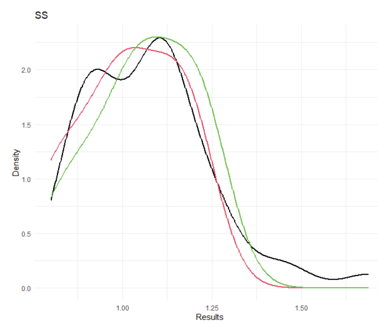
(a) Services -Employees



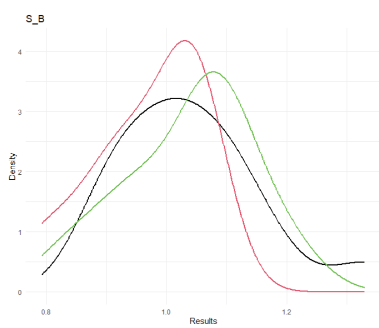
(b) Services - Business Units



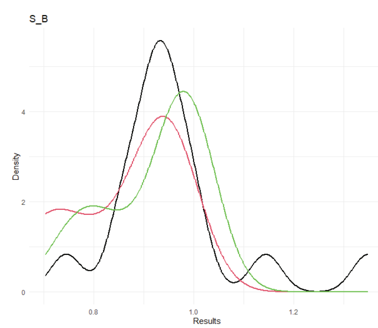
(c) Specialized Supplier - Employees



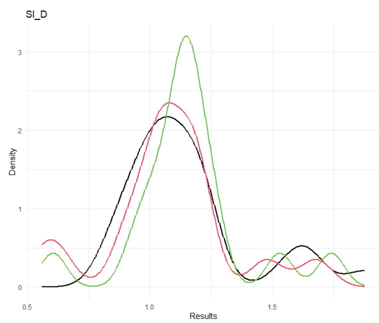
(d) Specialized Supplier - Business units



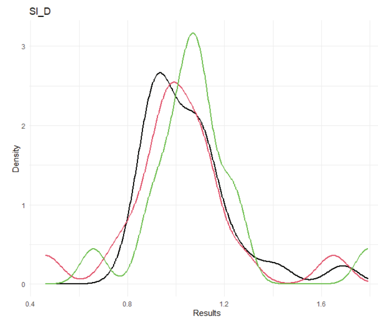
(e) Science Based - Employees



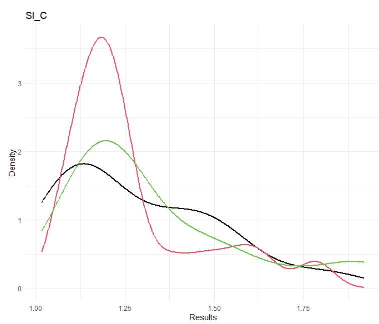
(f) Science Based - Business units



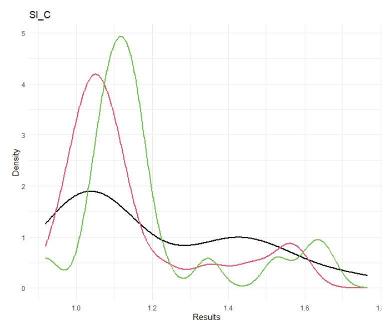
(g) Scale Intensive D. -Employees



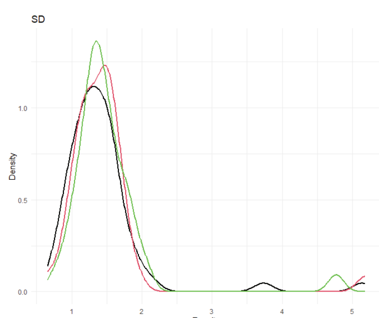
(h) Scale Intensive D. -Business Units



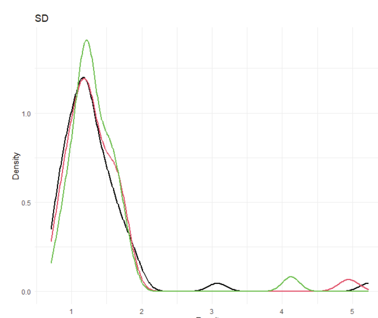
(i) Scale Intensive C. -Employees



(j) Scale Intensive C. -Business Units



(k) Supplier dominated -Employees



(l) Supplier dominated -Business Units

Figure 3: Sectors distribution of parameters proxy within each Pavitt Class. Red line for 2001, green for 2011, blue for 2019. On the right results from employee analysis, on the left on the Business units.

To study the stability of the parameter across years, a rank correlation coefficient analysis has been also performed between the parameter values of each 3-digit sector within each Pavitt class across years.

Class	Employees	Business Units
S_B	0.62	0.83
SD	0.94	0.97
Serv	0.94	0.93
SI_C	0.79	0.73
SI_D	0.83	0.79
SS	0.92	0.98

Table 14: Rank Correlation Coefficient

In line with the foregoing evidence, the exercise shows stability in the Services and Supplier Dominated classes, and the coexistence of agglomerative stability in terms of business units but slight turbulence in terms of employees for the Specialized Supplier class. Conversely, there is a relatively high instability in Scales Intensive ones, especially SI continuous, and Science-Based classes.

7 Conclusions and future perspectives:

The major novelty of this exercise lies in mapping the observed agglomeration patterns into technology-based sectoral taxonomies (drawing upon Pavitt, 1984). Indeed, since these are constructed on inter-sectoral differences in sources and patterns of innovation, their use in explaining agglomerative drivers can be seen as a proxy for the importance of innovative patterns themselves in firms' location propensities.

The evidence highlights the difference in the relative importance of agglomerative drivers across Pavitt classes, which is statistically significant and can be explained by the characteristics of the type and sources of knowledge used by sectors in each class, and the specific dynamics of knowledge diffusion. In general however, the agglomeration patter reveal some forms of increasing returns of different kinds, ranging from sheer economies of scale internalized within single firms/plants to localized knowledge-related interdependencies which are hardly compatible with conventional equilibrium interpretations.
Moreover, our analysis shed light on the relative weight of sector-specific externalities compared to urbanization drivers. This connects to the debate between "Marshallian" and "Jacobian" spillovers, showing how their relative importance is linked to sectoral innovative patterns. Thus, the inter-sectoral heterogeneity often found in the empirical literature can be drawn back to different patterns of innovation and knowledge accumulation.

Ultimately, our evidence on Italy supports the notion of "district-type" forces of agglomeration just in the case of Supplier-Dominated and (partly) Specialized Supplier groups of sectors, within an overall pattern of Italian de-industrialization. Moreover, we observe a general decline of the sectoral-specific agglomerative drivers between 2001 and 2011, followed by a partial recovery in 2019.

Admittedly, the methodology of analysis has serious drawbacks. In particular, the implicit assumption that every observation is the asymptotic equilibrium of some localization process is very difficult to digest especially in the light of a lot of intertemporal variability in distributions (except in the SD, SS, and Services Sectors). If genuine agglomeration forces are there they must hold over time, which implies also that history must count more than what must be assumed by the forgoing statistical test.
History plausibly matters also along the life-cycle of different activities, with the varying importance of agglomeration and concentration forces over time.
However, a more satisfactory account of these properties requires both the availability of longer and more desegregated time series and serious methodological refinement beyond finite-state stationary Markov processes.

We thank Ugo Gragnolati for his precious help in the estimates, and Martijn Smit for his comments on a previous draft. All usual caveats apply.

A. Appendix

A.1 Null Model 1

For both business units and employee data we simulate 200 distributions of firms yielding the distributions outlined by Equation 5.1. Subsequently, the parameters are estimated according to the model from e.q. 5.8. Thus we test the existence of agglomeration forces when comparing actual data with purely random agglomerations using the simulations as a null model.
The results in the following show that the coefficients for each sector in each period are significant.

	Buisness units		Employees	
Sector	Parameter	p_value	Parameter	p_value
101	0.71	0.00	0.71	0.00
103	0.65	0.00	0.66	0.00
11	0.51	0.00	0.50	0.00
111	0.68	0.00	0.68	0.00
112	1.07	0.00	1.00	0.00
12	0.77	0.00	0.75	0.00
132	0.20	0.00	0.14	0.00
14	0.68	0.00	0.70	0.00
141	0.43	0.00	0.41	0.00
142	0.56	0.00	0.52	0.00
143	1.14	0.00	1.01	0.00
144	0.71	0.00	0.67	0.00
145	0.52	0.00	0.44	0.00
15	0.46	0.00	0.43	0.00
151	0.63	0.00	0.62	0.00
152	0.70	0.00	0.67	0.00
153	0.55	0.00	0.47	0.00
154	0.19	0.00	0.19	0.00
155	0.61	0.00	0.68	0.00
156	0.53	0.00	0.53	0.00
157	0.68	0.00	0.65	0.00
158	0.81	0.00	0.80	0.00
159	0.60	0.00	0.66	0.00
160	0.82	0.00	0.82	0.00
171	0.58	0.00	0.59	0.00
172	0.56	0.00	0.56	0.00
173	0.73	0.00	0.73	0.00
174	0.88	0.00	0.80	0.00
175	0.79	0.00	0.72	0.00
176	0.64	0.00	0.61	0.00
177	0.69	0.00	0.63	0.00

– continues

Table A.1 – continues

	Buisness units		Employees	
Sector	Parameter	p_value	Parameter	p_value
181	0.87	0.00	0.80	0.00
182	0.82	0.00	0.65	0.00
183	1.20	0.00	1.12	0.00
191	0.69	0.00	0.69	0.00
192	0.83	0.00	0.73	0.00
193	0.57	0.00	0.54	0.00
20	0.33	0.00	0.27	0.00
201	0.64	0.00	0.63	0.00
202	0.72	0.00	0.70	0.00
203	0.70	0.00	0.64	0.00
204	0.77	0.00	0.75	0.00
205	0.84	0.00	0.69	0.00
211	0.94	0.00	0.92	0.00
212	1.02	0.00	0.89	0.00
221	1.42	0.00	1.51	0.00
222	1.15	0.00	1.11	0.00
223	1.28	0.00	1.29	0.00
231	0.71	0.00	0.71	0.00
232	0.99	0.00	0.97	0.00
233	0.74	0.00	0.75	0.00
241	1.02	0.00	0.88	0.00
242	1.01	0.00	0.89	0.00
243	1.05	0.00	0.99	0.00
244	1.34	0.00	1.10	0.00
245	1.17	0.00	1.08	0.00
246	1.07	0.00	0.96	0.00
247	0.98	0.00	0.90	0.00
251	0.97	0.00	0.93	0.00
252	0.90	0.00	0.80	0.00
261	0.90	0.00	0.74	0.00
262	0.66	0.00	0.57	0.00
263	0.73	0.00	0.69	0.00
264	0.68	0.00	0.65	0.00
265	0.75	0.00	0.70	0.00
266	0.67	0.00	0.63	0.00
267	0.64	0.00	0.56	0.00
268	0.92	0.00	0.82	0.00
271	1.07	0.00	0.96	0.00
272	0.94	0.00	0.87	0.00
273	0.96	0.00	0.87	0.00
274	1.00	0.00	0.85	0.00
275	0.99	0.00	0.92	0.00

– continues

Table A.1 – continues

	Buisness units		Employees	
Sector	Parameter	p_value	Parameter	p_value
281	0.87	0.00	0.80	0.00
282	0.87	0.00	0.78	0.00
283	1.22	0.00	0.99	0.00
284	0.90	0.00	0.83	0.00
285	0.81	0.00	0.79	0.00
286	0.80	0.00	0.74	0.00
287	0.87	0.00	0.74	0.00
291	0.94	0.00	0.88	0.00
50	0.46	0.00	0.42	0.00

Table A.1: Null model results

A.2 EG test

To illustrate the fact that EG index cannot clearly distinguish between intersectoral differences in agglomerative forces and "anti-urbanization" tendencies we conducted a simulation with two sectors. The first is perfectly distributed with a single company in each of the 10 locations, and the second has one company only in each location where there are less than 15,000 employees. Both sectors have zero intra-sectoral agglomerative tendency, but a repulsive drive from urbanized centers also characterizes the second. The results presented in Table A.2 show that the model assigns a positive agglomerative force to both, which is greater in the second sector (identified as anti-urb), as it has larger deviations from the null distribution.

Sector	Gamma	G	HH
Perfectly distributed	0.012	0.015	2.78e-03
Anti-Urb	0.015	0.017	1.46e-03

Table A.2: Ellison & Gleaser simple example

A.3 Significance test for Class differences:

In order to test the significance of the differences across taxonomies classes, sectors have been randomly assigned to different classes while keeping the number of sectors per class constant, repeatedly one thousand times per period. Subsequently, the mean and variance of the differences between each pair of simulated classes were estimated and used as statistics for the null model to estimate the significance level of the empirical differences.

Class		Employees data			Business units data		
Pairwise comparison		2001	2011	2019	2001	2011	2019
S_B	SD	0.267*	0.321***	0.308***	0.267**	0.397***	0.337***
S_B	Serv	0.048	0.082	0.045	0.048	0.239***	0.159**
S_B	SI_C	0.244*	0.265***	0.252**	0.244*	0.307***	0.26***
S_B	SI_D	0.177	0.187**	0.161*	0.177	0.272***	0.214**
S_B	SS	0.186	0.176*	0.172*	0.186	0.265**	0.222**
SD	S_B	-0.267*	-0.321***	-0.308***	-0.267**	-0.397***	-0.337***
SD	Serv	-0.218***	-0.239***	-0.263***	-0.218***	-0.158***	-0.178***
SD	SI_C	-0.023	-0.056	-0.055	-0.023	-0.09*	-0.077
SD	SI_D	-0.09	-0.133**	-0.147**	-0.09	-0.126**	-0.123**
SD	SS	-0.081	-0.145**	-0.136*	-0.081	-0.133*	-0.115*
Serv	S_B	-0.048	-0.082	-0.045	-0.048	-0.239***	-0.159**
Serv	SD	0.218***	0.239***	0.263***	0.218***	0.158***	0.178***
Serv	SI_C	0.196**	0.183***	0.207***	0.196**	0.068	0.101**
Serv	SI_D	0.129	0.106**	0.116*	0.129	0.032	0.055
Serv	SS	0.138**	0.094	0.127*	0.138**	0.025	0.063
SI_C	S_B	-0.244*	-0.265***	-0.252**	-0.244*	-0.307***	-0.26***
SI_C	SD	0.023	0.056	0.055	0.023	0.09*	0.077
SI_C	Serv	-0.196**	-0.183***	-0.207***	-0.196**	-0.068	-0.101**
SI_C	SI_D	-0.067	-0.077	-0.092	-0.067	-0.036	-0.046
SI_C	SS	-0.058	-0.089	-0.081	-0.058	-0.043	-0.038
SI_D	S_B	-0.177	-0.187**	-0.161*	-0.177	-0.272***	-0.214**
SI_D	SD	0.09	0.133**	0.147**	0.09	0.126**	0.123**
SI_D	Serv	-0.129	-0.106**	-0.116*	-0.129	-0.032	-0.055
SI_D	SI_C	0.067	0.077	0.092	0.067	0.036	0.046
SI_D	SS	0.009	-0.012	0.011	0.009	-0.007	0.008
SS	S_B	-0.186	-0.176*	-0.172*	-0.186	-0.265**	-0.222**
SS	SD	0.081	0.145**	0.136*	0.081	0.133*	0.115*
SS	Serv	-0.138**	-0.094	-0.127*	-0.138**	-0.025	-0.063
SS	SI_C	0.058	0.089	0.081	0.058	0.043	0.038
SS	SI_D	-0.009	0.012	-0.011	-0.009	0.007	-0.008

Table A.3: **Significance level of differences across classes.**

A.4 Significance test for differences across years

The significance test of the difference in means across years is obtained by calculating the mean and standard deviation of the parameter among the sectors of the various groups:

Class	2011-2001	2019-2011
S_B	-0.023402542108854***	0.039019271564972***
SD	0.00372129212587402***	0.0514789442163341***
Serv	-0.000754856830210926***	-0.0520490995531268***
SI_C	-0.0420960977879221***	0.0804764383557075***
SI_D	-0.0489475320722486***	0.0265019678703824***
SS	-0.0646647268609195***	0.0387294065877959***

Table A.4: Significance levels of the differences across years.

A.5 With population estimates

We checked the robustness of our analyses also using for Eq. 5.8 residential population as a proxy for the intrinsic attractiveness of the locations. The results are consistent with those obtained using the number of all businesses in the location.

Class	2001	2011	2019	2001	2011	2019
Serv	0,98	0,98	0,97	1,07	1,04	1,02
SS	1,22	1,13	1,18	1,15	1,10	1,11
S_B	0,97	0,94	0,97	0,91	0,84	0,87
SI_D	1,21	1,12	1,13	1,12	1,08	1,08
SI_C	1,28	1,21	1,25	1,23	1,12	1,14
SD	1,34	1,33	1,36	1,28	1,27	1,28

Table A.5: Parameters results with population proxy.

A.6 Industrial districts

The identification of industrial districts carried out by ISTAT is the result of a hierarchical four-phase process.

1. **Identification of predominantly manufacturing SLLs:**
   For each Local Labor System (SLL), the territorial concentration coefficient is calculated for each economic activity. Predominantly manufacturing SLLs are selected.

2. **Identification of predominantly manufacturing SLLs with small-medium enterprises (SMEs):**
   The territorial concentration coefficient for employees is calculated concerning the national average in micro (up to 9 employees), small (10 to 49 employees), and medium-sized (50 to 249 employees) size classes. Having an highest mean average value in one of the three employee classes (micro, small, and medium) defines a predominantly manufacturing SLL with small-medium enterprises (SMEs).

3. **Identification of the main industry of predominantly manufacturing SLLs with SMEs:**
   A territorial concentration coefficient is calculated for each industrial sector into which the manufacturing industry has been classififed. The prevalent industrial type is determined among those with a coefficient higher than the national average.

4. **Identification of districts:**
   One call district those SLLs where at least half of the employees in the sectors identified selected as prevalent in step 3 work in micro-small-medium enterprises. The employment in micro and small-sized production units of the main sector is higher than half of the employment in medium-sized production units when there is only one medium-sized production unit.

The industrial districts identified by ISTAT represent around a quarter of the nation's production system, constituting 23.1% of the total number of Local Labor Systems (SLLs), 24.5% of the workforce, and 24.4% of the production units. District-based manufacturing employment contributes to over a third of Italy's total manufacturing workforce. The "district industrial triangle" in Lombardy, Veneto, and Emilia-Romagna includes 70 districts (49.6% of the total), while Tuscany and Marche in central Italy host 34 districts (24.1% of the total), accounting for 73.8% of Italian districts.
These districts mainly specialize in machinery, textiles and clothing, home goods, leather and footwear, food, and jewelry, goldsmithing, and musical instruments, totaling 130 (92.2% of the total). Additionally, there are 5 districts specialized in the chemical and petrochemical industry, rubber and plastic products, 4 in the metallurgical industry, and 2 in the paper and printing industry.
The identification process was also extended to manufacturing SLLs with large local units, revealing 28 "crypto-districts" where a mix of large enterprise manufacturing and significant small and medium enterprise presence was noted. The most common specialization among these was in the mechanical industry (9 SLLs), with notable specializations in home goods (5 SLLs), food industries (4), chemical industries, rubber and plastic products, and textiles and clothing (3), paper and printing industries, and leather and footwear industries (2).

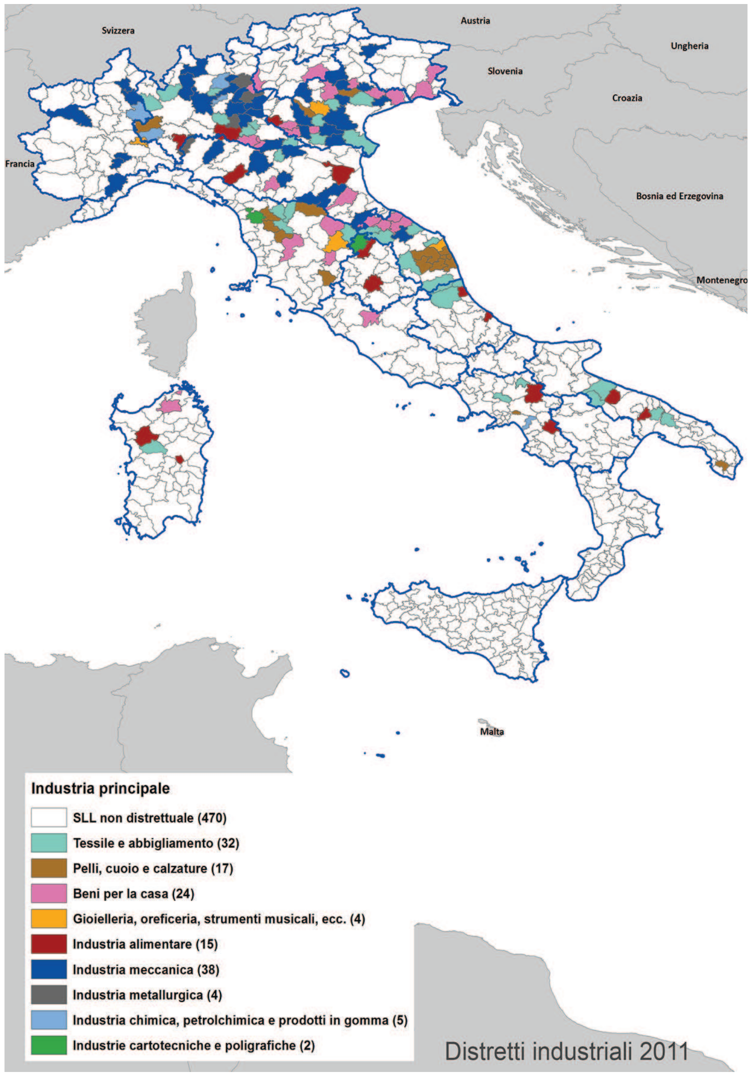


Figure A.1: Italian districts by ISTAT

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