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Abstract

The geographical distribution of innovative activities is an emerging subject, but still poorly understood. While previous efforts highlighted that different technologies exhibit different spatial patterns, in this paper we analyse the geography of innovation in the very long run. Using a US patent dataset geocoded for the years 1836-2010, we observe that – while it is true that differences in technologies are strong determinant of spatial patterns – changes within a technology over time is at least as important. In particular, we find that regional entry follows the technology life cycle. Subsequently, innovation becomes less geographical concentrated in the first half of the life cycle, to then re-concentrate in the second half.

Key words: technological regime, spatial patterns of innovation, life cycle, patents, US

1. Introduction

Innovation is more geographically concentrated than other human activities. Whereas specialized technology hubs in Silicon Valley or Kendall square are obvious examples, the phenomenon is not limited to a few special innovative regions, but extends to all innovative activities in general (Asheim and Gertler, 2005). This brings the question: what does determine the geographical distribution of innovative activities?

The interest of economics and innovation scholars in the geographical dimension of innovation activities has been growing in the last few decades (Jaffe et al. 1993; Feldman, 1994; Audretsch and Feldman, 2004; Breschi and Malerba, 2005). Similarly, the dynamics of knowledge production and diffusion has become a core topic in economic geography (Asheim and Gertler, 2005; Boschma, 2005; Cooke, 2001; Essletzbichler and Rigby, 2007). This has generated a fruitful cross-fertilization between these two academic communities and has contributed to the emergence of a cross-disciplinary research area named the *Geography of Innovation* (henceforth GI). A central tenet in this line of research is that knowledge spill-overs are spatially localised. Rooted in the Schumpeterian and evolutionary economics tradition (Nelson, 1993; Lundvall, 1992), this literature conceptualises innovation as a systemic process, which is the outcome of interactions and feedbacks between a variety of actors - i.e. public and private - and sources of knowledge, including universities and Public Research Organisations (Asheim and Gertler, 2005). The geographical implication of this theoretical argument is that physical proximity to knowledge sources facilitate the access, exploitation and diffusion of knowledge and eventually accelerates the innovation activity locally (Audretsch and Feldman, 1996b; Breschi and Malerba, 2001). It descends that regions hosting more innovative firms and relevant sources of knowledge have higher chances to be at the forefront in the next round of innovation as compared to firms in less innovative regions (Breschi, 2000: 214). This cumulative process is peculiar to how knowledge accumulates and has relevant geographical consequences: it triggers a self-reinforcing process of clustering, which eventually leads to uneven distribution of innovation activities over space (Breschi and Malerba, 2001).

Another theoretical claim of this literature is that the scope of possible innovative activities is bounded by the cognitive and technological knowledge owned by actors who contributed to their development (Breschi et al. 2003). From a geographical perspective, the crucial implication is that regions can successfully diversify in activities (e.g. products, technologies or industries) that are *related* to the pre-existing set of capabilities present in the region (Boschma, 2017; Rigby, 2015). In other words *path dependence* strongly shapes the direction of technological change (Dosi, 1988).

Several studies have contributed to understand the clustering of innovation activities as well as how regions diversify in new technological activities (Breschi and Malerba, 2005; Feldman et al. 2005; Rigby, 2015; Kogler et al. 2013; Boschma et al. 2014). However, relatively little attention has been devoted to investigate jointly the *sectoral and* the *geographical* dimensions behind these processes, in particular from a long-term perspective. A notable exception is the work of Breschi (2000), where technological specific factors (i.e. *technological regime*) are used to characterise different spatial patterns of innovation.

While building on the intuition of Breschi (2000), this work extends his analysis by adopting a very long-run perspective on the determinants of the geography of innovation. More specifically, we analyse the spatial patterns of innovation of US metropolitan areas over a period of almost 200 years (1836-2010). This allows us to go beyond the usual static approach adopted in most empirical works on Schumpeterian patterns of innovation (Breschi et al. 2000; Castellacci, 2007; Malerba and Orsenigo, 1996 and 1997).

The long-run perspective proves to be crucial. We find that, indeed, the geography of innovation varies by technology. However, changes over time within any given technologies are – so we find in this paper – as important, or even more important, than between-technology differences. We show that technologies, strikingly, have life cycles that can last over 150 years (see section 5). This means that short time-series dataset of 20, 30, 40 years may not be able to pick up the strong trends that we observe.

The empirical analysis draws on an original dataset of historical US patents (HISTPAT) (Petralia et al. 2006), which provides accurate information on the location of the main inventor, the technological classes of the patent and the year of application of the patent. Patents data from HISTPAT are used to build the main variables of analysis. The spatial patterns of concentration, diversification and ranking of innovators are built following the empirical work of Breschi et al. (2000) and Breschi (2000). For the determinants of the spatial patterns of innovation, we use technological regimes as measured in Park and Lee (2006) – with minor modifications explained in section 4.

We find that we can explain spatial patterns of innovation, with a remarkable degree of accuracy using technological regimes. In particular, *technological opportunities* (measured as flow of new patents in a class) closely tracks movement in geographical *concentration*, in *entry* of new regions, and in the *stability* of regional leaders. Other technological regimes (such as *cumulativeness* and *complexity*) also play an important, although smaller, role.

The paper is structure as follows: section 2 discusses the concept of technological regimes, as a way of describing the underlying features of a technology. Section 3 outlines a theoretical framework to imagine how technological regimes might influence the geography of innovation. Section 4 describes the data and the main variables we employ in our analysis. Section 5 presents the main results and their robustness. In section 6, we reflect on how the long-run perspective can change our interpretation of the determinants of spatial patterns of innovation. We conclude the paper in section 7, indicating some additional avenue of research.

2. Technological regimes

The notion of *technological regime* has been used in the innovation literature to characterise different technological environments, and it is usually defined as the combination of four elements (Breschi et al., 2000; Malerba and Orsenigo, 1996 and 1997): technological opportunity; appropriability conditions; knowledge cumulativeness and properties of the knowledge base.

Technological opportunities are identified with the external and internal sources of knowledge which feed the innovation process in a given industry/technology. Overall, they influence the speed and intensity of technological change in a specific knowledge environment. In the words of Breschi et al. (2000) they are defined as the probability of innovating per unit of investment in search (pag. 391). Higher opportunities reflect an environment which is favourable to innovation; therefore they provide firms strong incentive to engage with research activities. Overall, higher opportunities correspond to a higher rate of technological change.

Appropriability conditions indicate the extent to which innovation is protected from imitation. They impact on the profitability of an innovation and ultimately on the firms' incentive to invest in R&D. Higher appropriability means higher protection, which translates into higher rents for firms. However, this positive individual effect is counterbalanced by the reduction of knowledge spillovers to other firms: therefore appropriability may have a negative impact on technological change at sectoral level.

The *cumulativeness* of knowledge indicates that the innovation activity undertaken today builds on past innovation. It signals the incremental and bounded nature of the learning process. Therefore it also sets the boundaries of technological change and its path dependent character (Dosi, 1988). Since every new piece of knowledge is developed around some *related* knowledge base, firms innovate mostly along specific trajectories (Breschi et al. 2003).

The nature of the *knowledge base* is defined around a set of properties which includes specificity, complexity, tacitness and independence. Higher degree of tacitness, specificity and complexity imply less opportunity for knowledge diffusion, and in turn lower innovation activity. Conversely, higher independence may favour the wider diffusion and adoption of technology by other firms and eventually has a positive effect on innovation at sectoral level.

Such a composite notion of technological regime has been widely applied to explain the dynamics of industries and markets, and in particular to characterise the so called Schumpeterian patterns of innovation (Cohen and Levin, 1989; Malerba and Orsenigo, 1996; Nelson and Winter, 1982; Winter 1984). The literature has identified two main of such patterns: Schumpeter Mark I or *widening* pattern is characterised by frequent innovation, low concentration of innovators, high entry rate and where small firms drive the innovation process; Schumpeter Mark II or *deepening* pattern is characterised instead by high stability of entry rates, high concentration of innovators and markets, which are dominated by large corporations (Breschi et al. 2000; Schumpeter, 1934 and 1942).

Empirical studies have shown that the above patterns differ significantly across sectors, while they are mostly invariant across countries (Breschi et al. 2000; Castellacci, 2007; Castellacci and Zheng, 2010; Malerba and Orsenigo, 1996 and 1997; Montobbio, 2003; Park and Lee, 2006). They have found that a Mark I pattern tends to prevail among traditional sectors, like furniture, agriculture as well in sectors relying on mechanical technology (e.g. equipment, ship building, machine tools). On the other side, a Mark II pattern is more often found in high tech or complex sectors (among others aviation, biotech, electronics, computers). Breschi et al. (2000) provides an empirical test of the association between technological regimes and Schumpeterian patterns of innovation. They find that higher technological opportunities are associated with a *widening* pattern (i.e. low concentration, higher entry rates and turbulence in the ranking of innovators): firms that spot such opportunities will undertake R&D activities, introduce new products and develop into new sectors. This latter entry dynamics will reduce market concentration and eventually will challenge the incumbents in the industry. Similarly, the findings on the impact of appropriability are consistent with theoretical predictions, whereby higher appropriability is associated with high concentration, low entry and a stable ranking of innovators. These conditions reflects the feature of a *deepening* pattern (or Schumpeter Mark II), which is usually associated with the presence of large established firms, with large R&D departments and strong oligopoly market power (Malerba and Orsenigo, 1996). The other components of the technological regime (i.e. nature of knowledge base and cumulativeness) are also proven to be important predictors of the sectoral innovation patterns (Breschi et al. 2000).

A geographical analysis using technological regimes can be found in Breschi (2000). He posits that sectoral and spatial patterns of innovation are intimately related. Using patent data from the European Patent Office (EPO) in the period 1978-91, this work shows that the spatial patterns of patenting differ systematically across technological classes. The analysis identifies the typical Schumpeterian patterns of innovation and associates them to spatial factors. The findings show that a *widening* pattern is characterised by low spatial concentration and cumulativeness of innovative activities. To this pattern are associated mainly patents in traditional technological classes. Another *widening* pattern, which includes mainly machinery and engineering technologies, is also identified and associated with low levels of spatial concentration and high spatial cumulativeness. Finally, a third pattern, which consists mainly of chemical and electronic classes, combines features of a *deepening* pattern with high degree of spatial concentration and cumulativeness. Overall, this empirical evidence shows that the cumulativeness of knowledge is one of the most important components of the technological regime and drives the process of geographical concentration of innovation activities.

In our study we build on these findings and share with Breschi (2000) the idea that the determinants of "a technological regime do not only affect the way innovative activities are differently structured and organised across sectors, but they may have consequence also at the geographical level" (pag. 215) . It can be argued that sector's specific features, such as the degree of tacitness of knowledge, greatly affects the way innovative activities are geographically organised. It has been indeed observed that innovative activities that mostly rely on tacit knowledge show a tendency towards geographical concentration (Asheim and Gertler, 2005; Audretsch and Feldman, 1996b). On the same vein, it can be noted that technological opportunities are differently distributed across space: for example only some regions host relevant sources of knowledge (e.g. universities), and because of that they may be able to attract innovative firms. This self-reinforcing process does not only affect the innovative performance of individual firms, but also how the organisation of innovative activities unfolds over space.

In addition, we can argue changes over time within any given technologies along its life cycle are as relevant as between-technology differences. The sectoral and spatial patterns of innovation observed in a given time period reflect the peculiar stage of development of an industry and its core technology in that specific timeframe. As shown by the literature on industry life cycle, at different stages of development of an industry correspond different opportunities, levels of concentration and entry patterns (Klepper, 1996; Audretsch and Feldman 1996a). The relevant external sources of knowledge and the nature of the knowledge involved also vary according to the maturity of a sector and its technology (Klepper, 1996 and 1997; McGahan and Silverman, 2001). Breschi et al. (2000) acknowledged indeed that "a technological environment characterised by specific opportunity conditions may be related to a specific *stage* (*italics* added) in the development of an industry" (pag. 391, footnote 4). However, a dynamic perspective is rarely found in the literature on technological regimes[1].

While building on the above literature, we extend it by providing a systematic framework to test the relationships between each component of a technological regime and its spatial patterns of innovation. More in details, we test the effect of each component of a technological regime both on the clustering of innovation activities and on the diversification opportunities of regions. We also provide a characterization of the spatial concentration of innovation overtime.

3. Technological regimes and spatial patterns of innovation

In our analysis we characterise the spatial patterns of innovation according to three main indicators: the spatial concentration of innovation, which measures the geographical concentration of technological activities across regions; the spatial entry of regions, which indicates whether a new technology appears in a region; the stability in the raking of innovative regions, which captures the changes in regional innovativeness. Not surprisingly these indicators show a close resemblance to those used in the

[1] Breschi et al. 2000 keep constant the determinants of technological regimes in their empirical analysis. Empirical studies that looked at technological regimes in such a dynamic perspective are Audretsch and Feldman, 1994 and McGahan and Silverman, 200)

literature on Schumpeterian patterns of innovation (Breschi et al. 2000). However, a note of warning is needed: the mechanisms underpinning the relation between the above spatial processes and the components of a technological regime may differ from the mechanisms driving the Schumpeterian patterns discussed in the earlier literature. Therefore, in this section we set out specific theoretical arguments to unravel the relationships between technological regime and the spatial patterns of innovation. For each component of a technological regime (i.e. technological opportunity, appropriability, cumulativeness, nature of knowledge base) we discuss how it potentially relates to the indicators of spatial patterns of innovation (i.e. spatial entry, spatial concentration and stability of innovative regions). A summary of these relationships is presented in Table 1. At the end of this section we will briefly elaborate on the relation between the spatial concentration of innovation and the technology life cycle.

Technological opportunities

A technological environment that is favourable to innovation positively affects the entry of new firms, because the firms' returns of R&D increase as well as the quality and variety of knowledge sources (e.g. research centre, universities) they can tap into. Higher firms entry translates into more potential innovators, which are possibly distributed across different regions. If the latter is true, an increase of entry should lead to a decrease in the geographical *concentration* of innovation activities. However, as argued in Breschi (2000), higher opportunities may favour incumbents when they are able to identify earlier than newcomers these new opportunities and move quicker into these emerging markets/technologies. Under this latter scenario, when new opportunities come up the technological gap between incumbents and newcomers will be growing instead of closing. Therefore, we can claim that higher technological opportunities may be associated also to lower entry of firms and higher geographical concentration.

The effect of *spatial entry* (i.e. when a region develops a new industry/technology) depends on whether technological opportunities are either spatially distributed or concentrated. If for example a new university or laboratory is established in a region that is *already* active or specialised in that technology (or in related ones), so it can be regarded as an incumbent, then this region may attract additional innovators that trigger a cumulative process of concentration that will ultimately let the region to make a big leap over other competing regions. At the end of this process we will most likely observe a growing concentration and less spatial entry. In short, higher technological opportunities can generate also lower *spatial entry*, whereby incumbent regions are those benefiting most from new technological opportunities.

As for the impact of technological opportunities on the stability *ranking* of innovative regions, the effect depends on the above dynamics of spatial entry. If higher opportunities favour the incumbent regions over the newcomers, spatial entry will decrease and in turn this will lead to higher geographical concentration. This latter outcome will favour stability. On the contrary, if higher opportunities trigger the entry of newcomers (i.e. regions), the effect will be disruptive, and we should observe the emergence of a new ranking of innovative regions.

To sum up, the relation between technological opportunities and geographical concentration is an ambiguous one: it can be either positive or negative. Similarly, the impact of technological opportunities on spatial entry and on the stability of ranking of innovators can be either way, depending on *where* these opportunities emerge in the geographical space.

Appropriability conditions

The tightening of the appropriability conditions usually reduces the diffusion of knowledge spillovers in the industry. At sectoral level, this can translate into a slowdown of technological change. Incumbent regions (firms) will benefit most from such technological environment. Eventually this will lead to lower sectoral, but also lower *spatial entry* as well as higher *geographical concentration.* The extent of these latter spatial effects depends on how much knowledge spillovers are localised. The more they tend to be localised, the higher the impact on spatial entry and concentration. Higher appropriability conditions also imply that already innovative regions will be able to raise higher entry barriers and in turn safeguard their leadership in the industry. Therefore, it can be argued that the *spatial ranking* of innovative regions will not change with the increase in the protection of innovation.

Cumulativeness

At sectoral level, when new knowledge strongly depends on previous cumulated knowledge, i.e. cumulativeness is high, we can expect that all firms in that particular industry will benefit from it, since they share these externalities and build on them their future innovation activity. This can translate in higher *geographical concentration*, assuming that knowledge spillovers are highly localised. We will also observe lower *spatial entry,* given that incumbents are those that mainly benefit from these spillovers, so the *spatial ranking* of innovators will stay unchanged.

The nature of knowledge base

The nature of the knowledge base is a crucial dimension of a technological regime that affects the overall ability of firms to access and exploit opportunities and externalities. The prevailing properties will shape the form and speed as well as the spatial scope of knowledge diffusion. The property of knowledge will also affect the protection tools used by firms and the extent to which knowledge is cumulative. Three main properties are usually identified in the literature: degree of tacitness, complexity and independence. The more a piece of knowledge is embodied in artefacts or individuals (i.e. tacit), built on different knowledge domains (i.e. complex) and part of a system (i.e. less independent), the more is difficult to share it across actors and space. Therefore, it can be argued that the higher the tacitness, complexity and interdependence of knowledge, the higher the likelihood that innovation activities will be spatially concentrated. These features will also act as entry barriers for newcomers (both firms and regions), so leading to a situation in which incumbent actors (either firms or regions) will maintain their leadership. Therefore, we can argue that to a higher degree of the above knowledge features corresponds less *spatial entry* and a stable *spatial ranking* of innovators.

Table 1 - Technological Regimes and Spatial Patterns of Innovation: expected relationship

Technological Regime	*Spatial Pattern of Innovation*		
	Concentration	*Entry*	*Stability*
Opportunity	+/-	-/+	+/-
Appropriability	+	-	+
Cumulativeness	+	-	+
Complexity	+	-	+

Spatial patterns of innovation along the technology life cycle

The spatial patterns of innovation along the life cycle of a technology can be described using a diffusion curve which reproduces the stages of an industry life cycle, i.e. emergence, take off and maturity/fall (Klepper, 1996; Audretsch and Feldman, 1996a). Typically, the initial stage is associated to the entry of new and small firms, as depicted by a Schumpeter Mark I pattern or entrepreneurial technological regime (Winter, 1984). At this stage, innovation mainly concerns products, with designers and engineers exploring and solving the technical failures and bottlenecks of a technology (Perez and Soete, 1988). Knowledge is prevalently tacit, and the closeness to knowledge sources is crucial to address the variety of technical problems present in the early stages of technological developments. This phase is inherently turbulent, where the demand, functions and scope of a technology are not defined yet and subject to rapid change. The prevalence of tacit knowledge, along with the need of quick and intense interactions with knowledge sources, indicates that innovation activity is geographically localised in this stage (Audretsch and Feldman, 1996a). Therefore, we can argue that a spatial pattern characterised by high geographical concentration prevails in the initial stage of technological development.

During the take-off, the features of a technology are clearly defined, demand conditions are set; therefore we observe a rapid market growth. The focus of attention shifts from product specifications to the production process. Efficiency gains can be achieved by optimising plant production and organisation. Technical knowledge becomes increasingly standardised, while experience and skills needed for producing it (i.e. know-how) are now accumulated in firms' production units, so still far from standardisation (Perez and Soete, 1988). If this latter know-how is strongly embedded in firms and spills over only locally, we can still observe a tendency towards geographical concentration.

When the technology reaches maturity both technical and scientific knowledge are codified and easily transferrable over space. Similarly, production know-how becomes embedded in the technology and codified in manuals or the like, with explicit protocols and procedures. We can expect wider diffusion and/or imitation, with knowledge travelling over space much more easily that in the previous phases of the life cycle. The maturity phase corresponds to a Schumpeter Mark II pattern (Malerba and Orsenigo, 1996), or *routinized technological regime* (Winter 1984), characterised by the presence of large incumbent firms with high entry barriers to newcomers (Audretsch and Feldman, 1996).

The Schumpeter's Mark I and II patterns (Schumpeter, 1934 and 1942) reflect the evolution of the European and American industrial structures between the end of nineteen and the mid-twenty century respectively. Our aim is to reproduce these and post WWII other patterns drawing on more than 150 years patent data time series (i.e. 1836-2010). We can expect that spatial concentration of innovation will show differences overtime that are as relevant as those observed across technological sectors. A characterisation of these patterns for a selected group of technological classes will be provided in section 5. After that we will investigate the how technological regime affect these spatial patterns.

4. Data, methods and variables

4.1 Overview

Patents data from HISTPAT-US are used to build the main variables of analysis (Petralia et al., 2016). This dataset collects historical US patents from 1836 to 1975 and it also contains information on the geographical (county-level) location of inventors, as well as information on the patent class. We merge HISTPAT-US with the NBER patent dataset (Hall et al., 2010) to obtain a long, uninterrupted data series of patents that spans for almost two centuries. We argue that this perspective in the very long run allows to reveal hidden connections between technological regimes and spatial- Schumpeterian patterns of innovations.

The spatial-Schumpeterian patterns are built following the empirical work in Breschi et al. (2000). We employ number of indicators to capture the following concepts

1) Concentration: capturing the *geographical* concentration/dispersion of innovation activities. Particular care is dedicated to its measurement (see section 4.2);
2) Entry: to look at how many new patents are not from incumbent regions;
3) Rank-Stability: to measure the degree to which leading regions maintain their role of innovators over time.

The variation exploited in the analysis is by decade-technological class, technological class divides patents among over 400 3-digit technology classes. The choice of using decades (when years are available) has the advantage of pooling somewhat sparse patent data. It also helps in the design of some indicators (e.g. rank-stability, see section 4.2). The regional level at which indicators are computed can be either at county level or at state level.

The technological regimes are measured following, to a large extent, Park and Lee (2006).

a) Opportunity: captured as the total size of innovative activity. As we will discuss, this is a quantity that not only varies across technology, but has a particularly strong and relevant dynamic within technology, over time. In fact, it appears to reflect the life cycle of a technology;
b) Appropriability: measured through self-citations;
c) Cumulativeness: measured as the steepness of the convergence term in time series, or, alternatively, as the share of persistent innovators;
d) Complexity: as the average number of secondary classifications in patents within a primary technological class.

4.2 Dependent variables: spatial-Schumpeterian patterns of innovation

Concentration

We argue that, in the long-run dynamic context of our analysis, an ideal measure of spatial concentration must have the following properties

P1. Be neutral to the redefinition of geographical boundaries of the US;

P2. Be consistent with alternative measures.

Property P1 must be binding in our context since the dataset cover years of westward expansion of the US, which gradually extends the set of states and counties in the US.

Property P2 is important to make sure of the robustness of our results.

Perhaps, the three most popular choice for spatial concentration at the region level are the Gini, the Theil and the Herfindahl-Hirschman Index (HH, henceforth). We notice that the Gini and the Theil do not have property P1. To see this, imagine that all innovation in the textile manufacturing is shared equally between New Jersey and Massachusetts. We can express the Theil index as

$$Theil_{it} = \ln(N) - \sum_{r=1}^{N} \left(s_{rit} \ln \left(\frac{1}{s_{rit}} \right) \right),$$

where s is the share patent of technology class i in region r (in the example s is 0.5 for New Jersey and Massachusetts and 0 for the rest). Growth in concentration would be registered for the simple fact that a new state is counted in the union (e.g. N goes from 49 to 50).[2]

While one could say that concentration is indeed larger in this newly enlarged country, we argue that – since this is entirely due to a mechanical change in the `denominator' – it should not be captured. The HH index does not suffer from this issue, in fact we write

$$HH_{it} = \sum_{r=1}^{N} s_{rit}^2,$$

It can be noticed that summing additional zero terms has no effect on the index. We could be tempted to focus uniquely on *HH,* but in doing so we would not be able to check whether property P2 is satisfied, as we would not have comparable measure to test it against. Rather than discarding the Theil and Gini index, we opt to compute these indices while keeping N constant, to the largest set available. This forces P1 to hold for all indices which, in turns allows to increase comparability.

Keeping N constant makes, in fact, the dynamics of HH and Gini over time very similar. However, the Theil index is still not comparable (see figure A1 in appendix). Following the discussion in Jost (2006), the Theil index is only a proxy for concentration (diversity in their work) in the same way "[t]he radius of a sphere is an index of its volume but is not itself the volume" (p.363; Jost, 2006). The author argues that the Theil index (more precisely its analogue, Shannon entropy) should be modified by taking *exp(*index*)*, rather than the simple index. In our context, this seemingly minor change is enough, as testified in figure A1 in appendix, to get the Theil index to agree with HH and Gini.

By applying these careful modifications, we now have three indices of concentration that satisfy properties P1 and P2. We therefore focus our analysis on one index (Theil) and use the remaining two for robustness.

Entry

In Breschi (2000) an analogous variable is constructed by defining innovators at the film level. To make full use of the longitudinal extent of HISTPAT-US, we opt to ignore the role of assignees and focus instead on a variable aiming to capture entry of regions. As our interest lies on the geographical dispersion of innovation, we argue that this choice is desirable even if assignee data were available. We then define *entry* as

$$Entry_{it} = \frac{\sum_{r \in NEW_{it}} P_{irt}}{\sum_r P_{irt}}$$

Where P is the number of patents and NEW_{it} is the set of regions that patent for the first time in class *i in decade* t. In other words, the indicator is the share of patents originating from regions that patent for the first time in that technology.

Rank-Stability

To measure stability we follow more closely the work of Breschi (2000). The main challenge in our context is that we need, as for the other variable, a time-varying metric. We therefore resort to splitting a decade in two 5-year periods and then correlate the rank of innovative regions in the two periods. Formally

[2] For the Gini index, think for instance on how the Lorentz curve changes by adding regions.

$$Stability_{it} = \underset{r}{\mathrm{corr}}(rank(s_{ri,\tau 1 \in t}, s_{ri,\tau 2 \in t}))$$

Note that regions are ranked for each technological class, twice every decade. When the ranking in the first part of the decade is similar to the second part, it means that the technology is stable in the period.

4.3 Explanatory variables: technological regimes

Opportunity

Following Park and Lee (2006), we measure it simply as

$$Opportunity_{it} = P_{it}.$$

That is simply counting the number of patents in class, in a decade[3]. While this may appear simplistic, we find that – by capturing the size of the innovation market, both relative to other technologies and relative to the same technology in different stages of its life cycle – the indicator is one of the major explanatory factors of the geography of innovation.

Appropriability

We use self-citation over total citation (Jaffe et al. 1993; Park and Lee, 2006). As citations are not available in HISTPAT-US, to control for the role of appropriability on spatial patterns of innovation, we are constrained to restrict the analysis to the period 1970-1990, which is covered in the NBER patent citation dataset. Indexing assignee as *a*, defining patent citation as C_{odt} (with C=1 if patent *o* cites patent *d*), and *J* as the set of patents pairs that have at least one author in common – the indicator is

$$Approp_{it} = \frac{\sum_{d \in i} \sum_{o} (C_{odt} | \{o, d\} \in J)}{\sum_{d \in i} \sum_{o} (C_{odt})}$$

Cumulativeness

We measure it (following Park and Lee, 2006) as the share of patents held by persistent innovators over total patents.

$$Cumulat_{it} = \frac{PI_{it}}{P_{it}}$$

Where *PI* are patents held by persistent innovators, defined as assignees that – within decade *t* – have at least 4 patents in the first 5-year period, as well as at least another 4 patents in the second 5-year period (e.g. 1980-1984 and 1985-1989). The denominator denotes all patents in the class-decade. Note that, as for *appropriability,* the use of additional information (assignees in this case) forces us to restrict the analysis to the period 1970-1990.

As C*umulat* is limited to a short time frame, we test an additional indicator, taken from Breschi (2011). The idea is to measure the size of the mean-reversion term in a growth-level regression, this captures the stationary of the time series for a specific class in specific decade (using years to have variation within a class-decade combination).

[3] Note that we use specifications in level as well as in growth. In the latter case *opportunity* is more in line with the measurement in Park and Lee (2006).

$$Cumulat_{it}^{*} = \widehat{\beta_{it}}, \text{ computed with the model } \Delta P_{i,y\in t} = \beta_{it} P_{i,y\in t} + \varepsilon_{i,y\in t}.$$

Index $y \in t$ indicates a year within decade *t.* A separate model is fitted for each class-decade combination. Note that *cumulat** is the only variable that can have negatives. As we run our regressions with a specification in logs, we re-centre this variable by adding a scalar *s*=3. All other variables do not have negatives, but sometimes have a value of zero. As this is also true also for the dependent variables, we prefer to run the main regressions, conditioning on all the variables having positive values. As robustness check, we re-run the analysis with all observations, by adding a small (0.001) scalar to all observations. Our results (available upon request) hold to this alternative method for handling zeros.

Complexity

We capture the idea of complexity following the perspective on innovation highlighted by Fleming and Sorenson (2001): innovation can be seen as a recombination of different technologies. In this light, we can measure the complexity of a patent by counting the number of secondary classification listed in a patent. Defining that number as S_k for patent *k,* we measure complexity of a class, we write

$$Complexity_{it} = \frac{\sum_{k\in i,t} S_k}{P_{it}},$$

that is the average number of secondary classes among patents with primary class *i.*

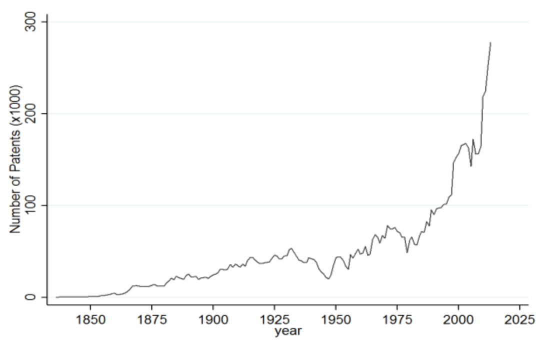
5. Empirical findings

In what follows we present the empirical findings of our analysis by looking first at the dynamics of the spatial innovation patterns (Section 5.1) and at its determinants (Section 5.2). In section 5.3 we carry out several robustness checks.

5.1 The long term dynamics of the US spatial innovation patterns

The growth in patenting has been remarkable since 1836 (see Figure 1). Although this historical trend is well known, less is known about its geographical and sectoral distribution. The information extracted from Histpat allows us to reconstruct the spatial and sectoral patterns of innovation since 1836 till today, unveiling the *within and between* sectoral heterogeneity.

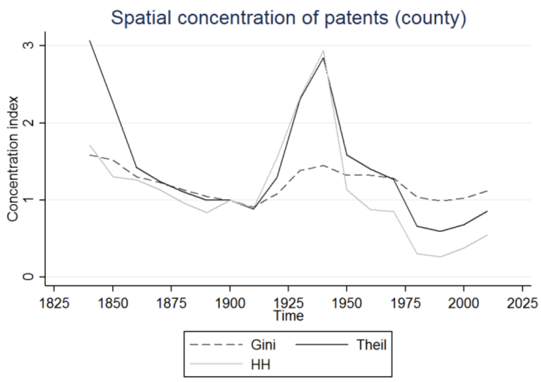
Figure 1 – Total patent flow over time.



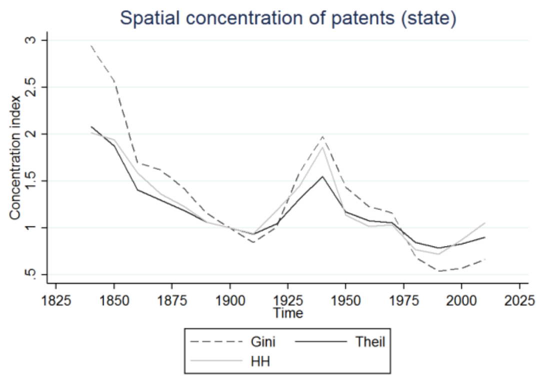
As shown in Figures 2a and 2b, geographical concentration of patenting fluctuated overtime both at county and State level. A first declining trend in geographical concentration can be depicted between the early nineteen till early twentieth century. These are the years of the entrepreneurial capitalisms described by Schumpeter in *Theory of Economic Development* (1934). Creative destruction is the main force driving structural change in those days. Following the literature on technological regimes, this pattern has been named as *entrepreneurial technological regime* (Winter, 1984) or Schumpeter Mark I (Malerba and Orsenigo, 1996), which are characterised mainly by the entry of new and small innovative firms and competitive markets. After the turn of the century concentration rises again till approximately WWII. Also in this latter case, the growth in spatial concentration is coherent with the so called Schumpeter Mark II or *routinized technological regime* (Winter, 1984; Malerba and Orsenigo, 1996). This is the historical period when the US economy was dominated by oligopolistic industries and large R&D labs started to become central in firms' innovation activities. After WWII, we can observe a decline in spatial concentration, which reflects the emergence of new technological trajectories related to new sectors and technologies (e.g. semiconductors), which were partly emerging in new regions. It was underway the gestation of a new techno-economic paradigm based on ICT which will geographically materialise with emergence of new clusters (e.g. Silicon Valley). More recently, since the early 1980 we observe a reverse trend towards concentration, which is best exemplified by the dominance of few innovation clusters, for example in industries such as pharmaceuticals, semiconductors, ICT and electronics (e.g. Boston, Silicon Valley, Austin).

Figures

2a



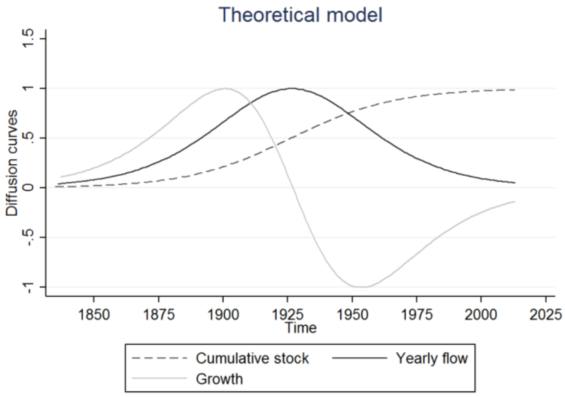
2b



In order to unveil the heterogeneity of the overall pattern illustrated above, we analyse the dynamic of individual technological classes over time. As shown in Figures 3a and 3b below, this dynamic describes a pattern that is remarkably close to either a logistic diffusion model or the product and industry life cycle (Fig.3a)

Figures

3a



3b

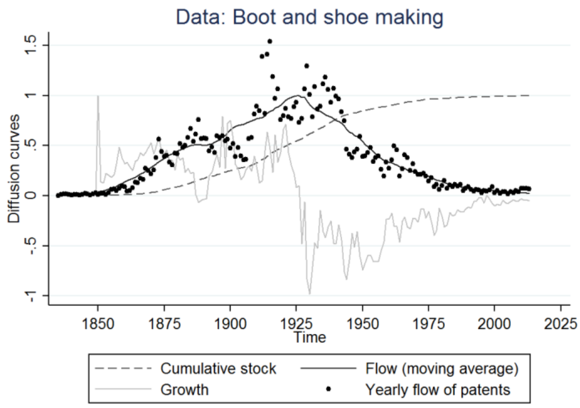
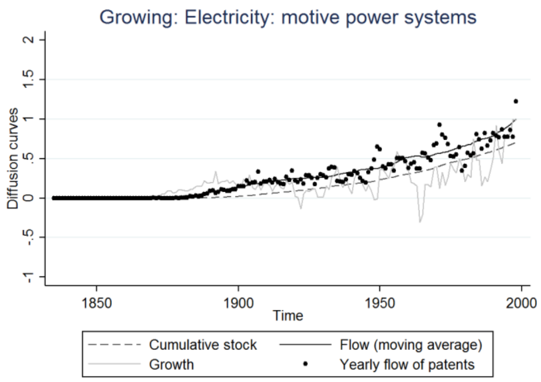


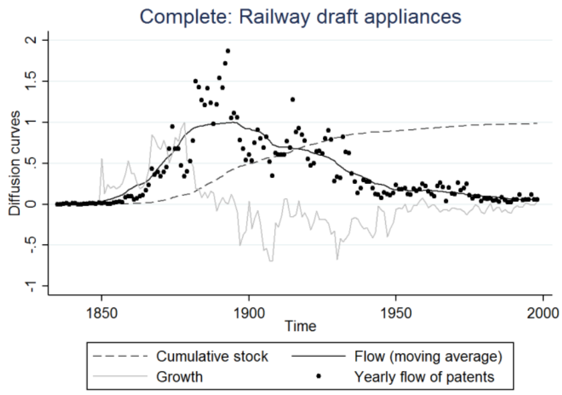
Figure 3b presents an exemplary case, the "boot and shoe making" technological class, which follows the typical S-shaped cumulative curve of the diffusion model. The example clearly illustrates a case where technology has achieved full maturity. Besides the diffusion curve, the data reproduce also the growth dynamics of a typical industry life cycle (Klepper, 1996), characterized by three main stages: emergence, take-off and maturity. After the emergence, rapid growth driven by entry is usually ending with what Klepper called a shake-out. The shake-out occurs at the peak of entry in the industry, and is followed by negative growth rates and decline in patenting/entry. However, not all technological classes follow the same pattern. Figures 3c-3e below identify three paradigmatic cases of technologies that are at different stages of the life cycle: take-off/growing; renewal/new paradigm; complete/ maturity /decline respectively (see Figures 3c-3e).

Figures

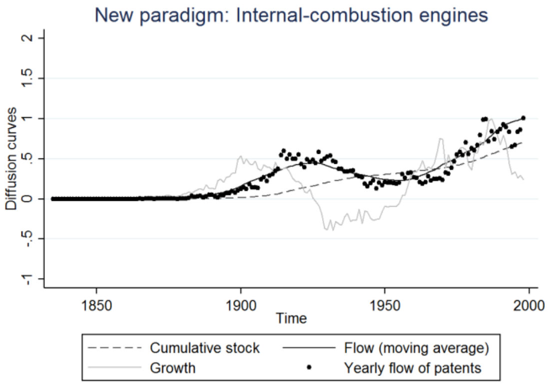
3c



3d



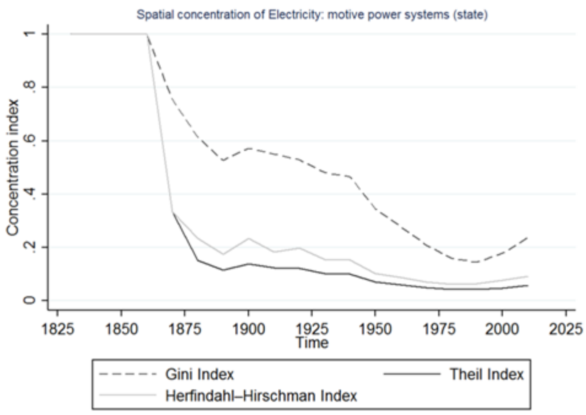
3e



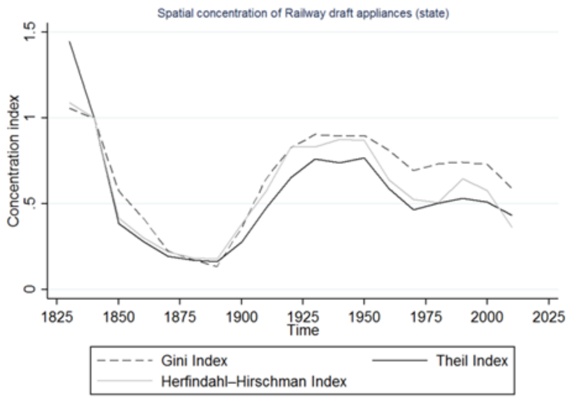
For example, *electricity power systems* represents a technological class still in its growing phase, which over more than 150 years has not yet achieved full maturity. On the contrary, the *railway appliances* class represents a typical mature technology which went through all the stages of the life cycle. Another peculiar example is given the by the *combustion engine* class. After reaching maturity, a new wave of entry gave rise to a renewal of this technology, which is now growing again.

Figures

4a



4b



The spatial concentration of technological classes, as those described above, follow patterns which are coherent with the different degree of maturity of their technologies. For example, the technological class "electricity" is still expanding. Coherently we observe that its spatial concentration has been declining steadily since its emergence. A mature technology like "railway appliances" shows a more complex spatial dynamic. A declining trend characterised its emergence and take-off stages, which ended in the early 1900s. After having reached the peak of entry, concentration increased quickly during the shake-out, which was followed by a spatial de-concentration during the maturity phase.

5.2 Technological regime and spatial patterns

In this section we analyse more in details the relation between each component of the technological regime and how they impact on the spatial patterns of innovation (i.e. spatial entry, geographical concentration, ranking of innovative regions). To correctly estimate the relation between technological regimes and spatial patterns, we include time dummies in all our regressions. This avoids that we pick up spurious relations and allows us to control for large trends, such as change in overall concentration of economic activities (which, as we show in figure A2, declines during the period of Westward expansion, and increase afterwards). Table 2 presents the baseline model, which includes the four components of a technological regime. In Table 3 we add an interaction term capturing the joint role of *cumulativeness* and *appropriability* conditions. The last specification presents the baseline model with all independent variable lagged (see Table 4).

Technological opportunities

In the first column of Table 2, the coefficient estimate of the variable *opportunity* shows a negative and statistically significant sign, which indicates that higher technological opportunities reduce the spatial concentration of innovation. This finding is coherent with the positive sign associated to the *opportunity* coefficient in the entry model (second column, Table 2) and suggests, in line with our claims, that higher technological opportunities provide regions (and firms therein) with strong incentives to diversify towards new technological classes. Entry of new regions will in turn make the geographical distribution of innovation activities less concentrated. Following this logic, we should observe also a shift in the ranking of regional innovators. Instead, the positive sign of the *opportunity* coefficient in column 3 (Table 2) indicates the opposite: higher opportunities reinforce the existing ranking of innovative regions. This latter finding suggests that incumbents are able to keep ahead of those laggard regions that for the first time entered new technological fields. Though surprising, we can explain this latter finding by noticing upon closer inspection that - especially in the first half of the life cycle (see Figure A3 in appendix) - innovation clusters were very stable overtime. This evidence indicates that while undoubtedly the growth of patenting favoured the entry of new regions, most innovative hubs remained anchored to established locations.

Table 2 – Technological regimes and spatial patterns of innovation: Baseline regression

VARIABLES	(1) theil	(2) entry	(3) stability
opportunity	-0.583***	0.576***	0.117***
	(0.0120)	(0.0129)	(0.00433)
approp	-0.0740***	-0.0162	0.00803
	(0.0184)	(0.0199)	(0.00643)
cumulat	0.242***	-0.0645***	0.0427***
	(0.0108)	(0.0122)	(0.00370)
complex	0.164***	0.0713*	0.0352***
	(0.0431)	(0.0420)	(0.0122)
Constant	-0.728***	0.196*	-1.089***
	(0.117)	(0.119)	(0.0406)
Observations	1,262	1,262	1,254
R-squared	0.723	0.787	0.765

Robust standard errors in parentheses. All variables in logarithm. Time dummies included
*** p<0.01, ** p<0.05, * p<0.1

Appropriability and cumulativeness

We predict that higher appropriability allows for greater protection of innovation, which is expected to lead to higher spatial concentration, lower entry and higher stability. We find that *appropriability* is only associated with concentration in the baseline model and with the opposite sign, compared to our expectations (see columns 1 to 3, Table 2).

These contradicting findings are however not surprising given that both theoretically and empirically the effect of appropriability on innovation outcomes is often vague (Levin et al. 1985; Breschi et al. 2000; Park and Lee, 2006). Theoretically, we know that higher appropriation provides higher protection from imitation; however, it also stimulates competition, because newcomers have stronger incentives to enter sectors where rents can be more easily appropriated. Empirically, measuring appropriability with self-citations, we potentially capture different effects. In particular, higher self-citations can signal that actors rely less on others' knowledge, and do so because they lack R&D resources. This finding has been found in particular in the case of latecomer countries (Park and Lee, 2006), but it can possibly apply also to latecomer regions more in general.

Table 3 – Technological regimes and spatial patterns of innovation: models with interaction term

VARIABLES	(1) theil	(2) entry	(3) stability
opportunity	-0.541***	0.532***	0.114***
	(0.0126)	(0.0131)	(0.00477)
approp	0.308***	-0.415***	-0.0261**
	(0.0482)	(0.0358)	(0.0110)
cumulat	0.420***	-0.250***	0.0260***
	(0.0258)	(0.0207)	(0.00740)
complex	0.136***	0.101***	0.0374***
	(0.0404)	(0.0384)	(0.0122)
apprcumu	0.101***	-0.106***	-0.00935***
	(0.0120)	(0.00960)	(0.00329)
Constant	-0.206	-0.348***	-1.137***
	(0.133)	(0.119)	(0.0397)
Observations	1,262	1,262	1,254
R-squared	0.745	0.808	0.767

Robust standard errors in parentheses. All variables in logarithm. Time dummies included
*** p<0.01, ** p<0.05, * p<0.1

A different interpretation of this unexpected finding descends from the way appropriability interacts with cumulativeness. Tighter appropriability conditions tend to be associated with high cumulativeness (Breschi, 2000; Dijk, 2000). We capture this relation by adding the interaction term *apprcumu*. As shown in Table 3, once *apprcumu* is included in the model, the relation between appropriability and geographical concentration becomes positive (now in line with expectations, see first column, Table 3), and such effect is stronger the higher the degree of cumulativeness. The relation between *appropriability* and spatial entry becomes negative and statistically significant (second column, Table 3). The impact of *appropriability* on the ranking of innovators is now negative and significant (see third column, Table 3). An hypothesis for these results could be that – contrary to our first intuition – entry and stability go hand-in-hand, meaning that periods of entry are also periods of consolidation for leading regions (and this is reflected on the fact that in all cases, except for *cumulativeness*, the coefficients of *entry* and *stability* have the same sign: see Table 3). However analysing to the lagged model in Table 4

– a model that partially addresses concerns of endogeneity buy looking at Granger causality – we observe that the results on *appropriability* are not robust. As further analysis in the next section confirms this (together with tables A5, A6 and A7 showing that *appropriability* has the lowest R^2 in univariate regressions), we conclude that *appropriability* is a weak determinant of the geography of innovation.

Turning our attention to the relation between *cumulativeness* and geographical concentration (first column, Table 2), our findings indicate a positive and statistically significant impact, as expected. When knowledge is path dependent, earlier innovators tend to maintain their leadership, so spatial concentration of innovation activities increases as observed. Similarly, the impact of *cumulativeness* on spatial entry is negative, confirming that laggards find more difficult to make their way into new technological fields (see second column, Table 2). Coherently, we also find that established innovative regions keep their lead over competitors, so the ranking of innovative regions does not change overtime (see third column). These findings become even stronger when the interaction term *apprcumu* is included (see Table 3).

Complexity

As far as complex knowledge is concerned, our findings show a positive association with geographical concentration, as expected. This provides some evidence that complex technologies tend to cluster in fewer locations than less complex ones. Surprisingly enough, we find a positive relation between entry and complexity (see second column, Tables 2 and 3). These findings seem to be counterintuitive and contradict recent evidence on the relation between regional specialisation and complexity (Balland et al. 2017). To be noticed that the variable *complex* is negative when included alone in the model. However, this relation fades away when lagging the independent variables (see column 2, Table 4). This reveals a potential reverse causality between entry and knowledge complexity: entry of new regions – with presumably different technological background – makes technology more complex. Complexity also appears to increase rank *stability* of innovative regions.

Table 4 - Technological regimes and spatial patterns of innovation: Lagged model

VARIABLES	(1) theil	(2) entry	(3) stability
opportunity (lagged)	-0.595***	0.536***	0.115***
	(0.0179)	(0.0225)	(0.00511)
approp (lagged)	-0.106***	-0.0354	-0.000793
	(0.0351)	(0.0389)	(0.00964)
cumulat (lagged)	0.235***	-0.0482**	0.0442***
	(0.0152)	(0.0191)	(0.00465)
complex (lagged)	0.124**	-0.00463	0.0511***
	(0.0614)	(0.0689)	(0.0162)
Constant	-0.696***	0.266	-1.100***
	(0.153)	(0.189)	(0.0429)
Observations	1,262	1,262	1,254
R-squared	0.642	0.602	0.686

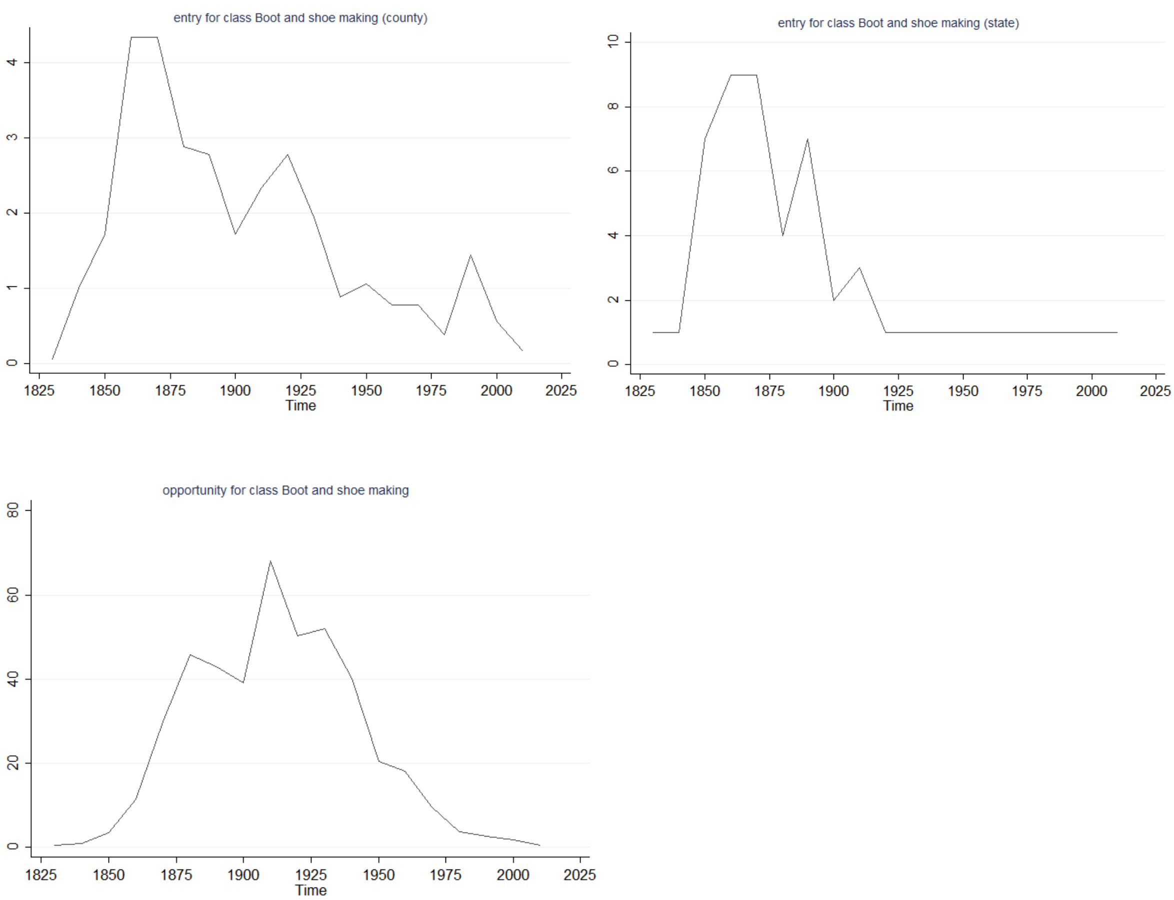
Robust standard errors in parentheses. All variables in logarithm. Time dummies included

*** p<0.01, ** p<0.05, * p<0.1

5.3 Robustness checks

We test the robustness of our results to a number of standard controls: we compare results at the county level with those at the state level. We try different measures of concentration. We analyse the within variation with a Fixed Effects model and a First Difference model. We extend the analysis to the full 1830-2010 period thank to univariate regression and an alternative indicator of *cumulativeness*. In fact, *cumulativeness* and *appropriability* are the bottlenecks in our analysis, forcing us to drop older observations. As we established that *appropriability* is a weak determinant of the spatial patterns of innovation, by using an alternative index for *cumulativeness,* we can perform multivariate analysis on a long-series of data.
First, we find that – using state data (see Table A3) – results are robust for *concentration* and *stability*, but less so for the remaining spatial pattern: *entry*. We believe that the state level is too broad to capture the *entry* dynamics properly. Figure 5 shows, with our working example on boots, why this the case. It can be easily seen that by 1925, every state that could innovate on boots has already entered. For counties, instead, entry continues to this day. Although entry peaks before opportunity, the two series are positively correlated – if we take entry at the county level. With entry at the state level, we observe that between 1850 and 1925 entry is declining while opportunity is growing: the two series are negatively related. We conclude that the coarser geographical division at the state level mechanically forces the *entry* index to peak much earlier than at the county level, resulting in the incorrect sign in Table A3.

Figure 5 – Entry dynamics for boot and shoe making



Alternative concentration measures show the robustness of our results with respect to concentration. The only marked difference is the effect of *appropriability* on the *Gini* index, which is opposite to the one we find with Theil and HH indices. This further confirms that *appropriability* does not explain spatial patterns of innovation in a satisfactory way.

Tables A1 and A2 test Fixed Effects and First Differences specifications. Results are remarkably robust for *opportunity* and *cumulativeness;* they are instead only relatively robust for *complexity* and *appropriability.* In this latter case, we mean that Fixed Effects and First Differences estimates are in line with the OLS benchmark, although the benchmark itself is not, as discussed, very robust.

Finally, we extend the analysis to the full period, either by using univariate regressions or by excluding *appropriabilty* and including the alternative indicator of *cumulativeness* in multivariate regressions. Tables A5, A6, A7, show the result of these exercises. We find that the two indicators of *cumulativeness* are consistent with one another in univariate regressions. However, univariate and multivariate results vary significantly for this indicator, suggesting that *cumulativeness* suffers from omitted variable bias in univariate regressions. Different is the case for *opportunity*, which remains consistent throughout. Univariate regressions also highlight that *opportunity* is the single most important determinant of innovation patterns with R^2 reaching as high as 0.9.

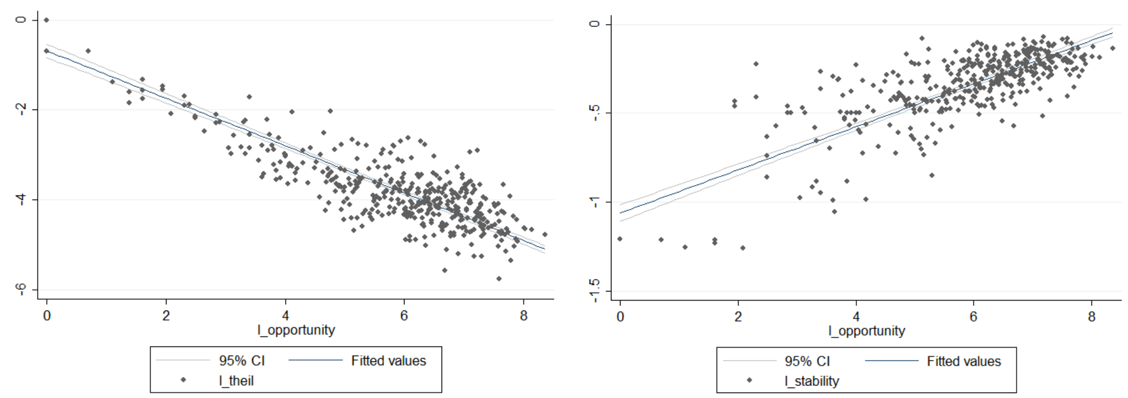
All in all, these checks bring us to conclude that *opportunity* has a consistent and extremely important role in determining the geography of innovation. C*umulativeness* and c*omplexity* also play a small but significant role, while *appropriability* only a weak one. We further discuss the remarkable role of *opportunity* in Section 6 below.

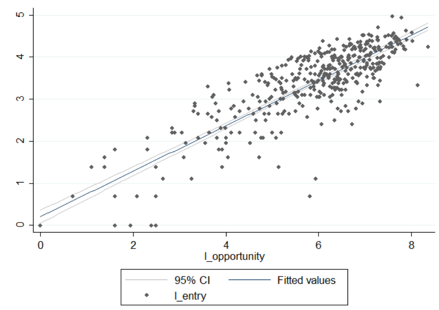
6. Cross-sectional and longitudinal impact of opportunity

How do we interpret the extremely strong relation between *opportunity* and the spatial patterns of innovation? Given the importance of this indicator – which in essence captures the size of a technological class – we think this question deserves a closer look.

Figure 6 provides one possible interpretation on the role of *opportunity*, which focuses on the cross-sectional differences. The figures depict the link between *opportunity* and the three main indicators of spatial innovation: *concentration, entry, stability.* To focus on the differences between classes we only show the bivariate relation in 1950 (the choice of the year is arbitrary, figures with a different decades are consistent and available upon request). The figure suggests the following: (1) larger technologies are more spatially spread; (2) larger technologies are conducive of more entry; (3) in larger technologies, leading innovative regions are harder to disrupt, so change in leadership is less likely. This third is perhaps the most surprising result, given that larger entry is expected to be a challenge for the leader. We propose that this might have to do with the fact that smaller technologies are less predictable, leadership is less consolidated, and new inventions are more likely to be disruptive.

Figure 6 - Concentration, Entry, Stability against Opportunity. Levels in 1950.

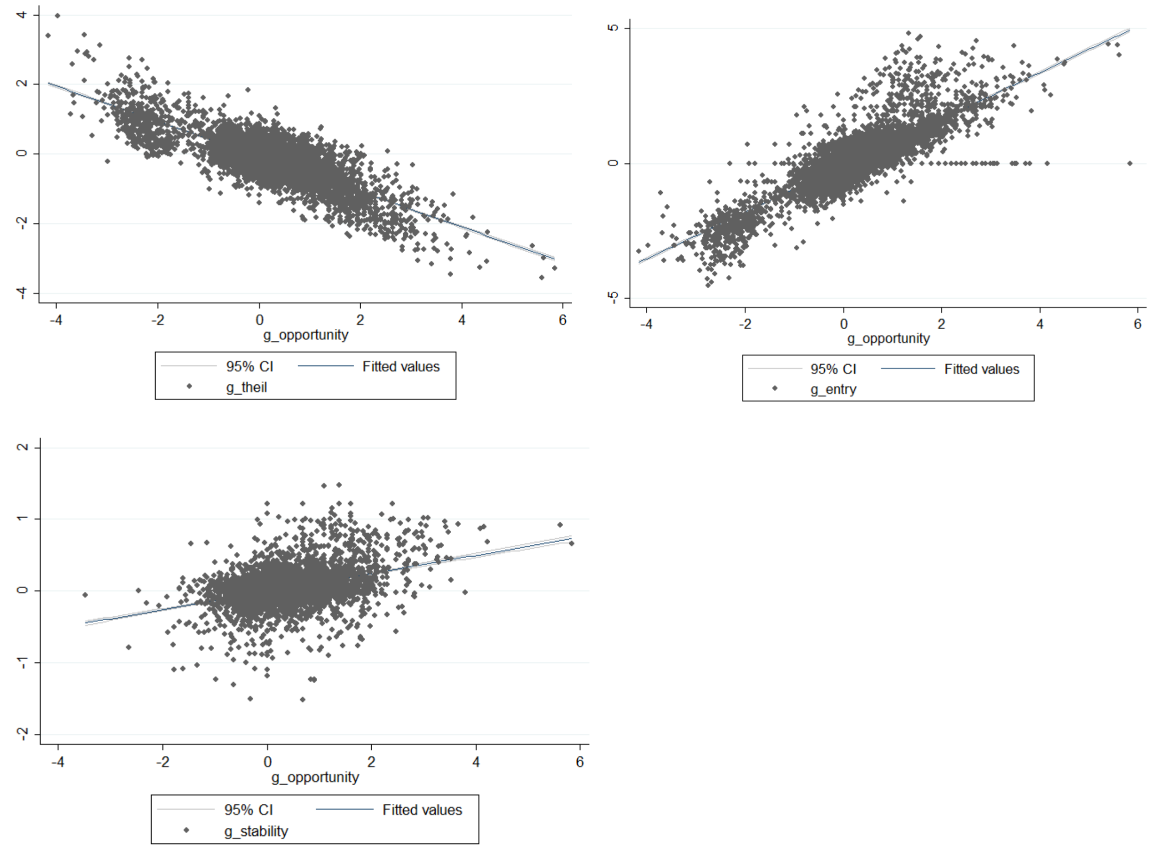




Top-left: concentration (Theil). Top-right: entry. Bottom-left: stability. All variables in logs.

This interpretation is even more meaningful if we think about opportunity longitudinally. Figure 7 shows this second take on the role of *opportunity*, by looking at the First Difference of all variables. It is evident the relations are as strong in differences as they are in level. While in principle one should not be surprised, we note that – given the behaviour of *opportunity* that we observed within a class, overtime (see Figures 3a-3e) – taking the longitudinal perspective opens up a discussion on how the spatial patterns of innovation evolve along the technology life cycle.

Figure 7 - Concentration, Entry, Stability against Opportunity. Change VS change.

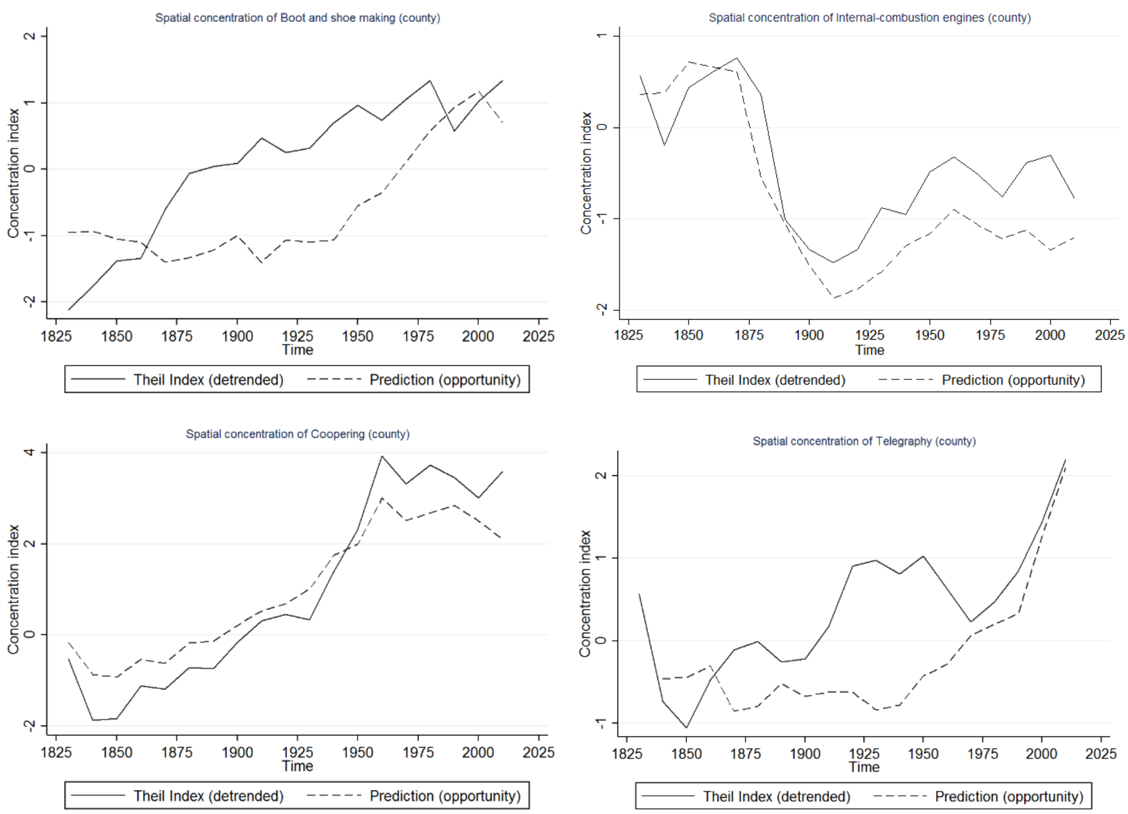


Top-left: concentration (Theil). Top-right: entry. Bottom-left: stability. All variables in differences (of logs).

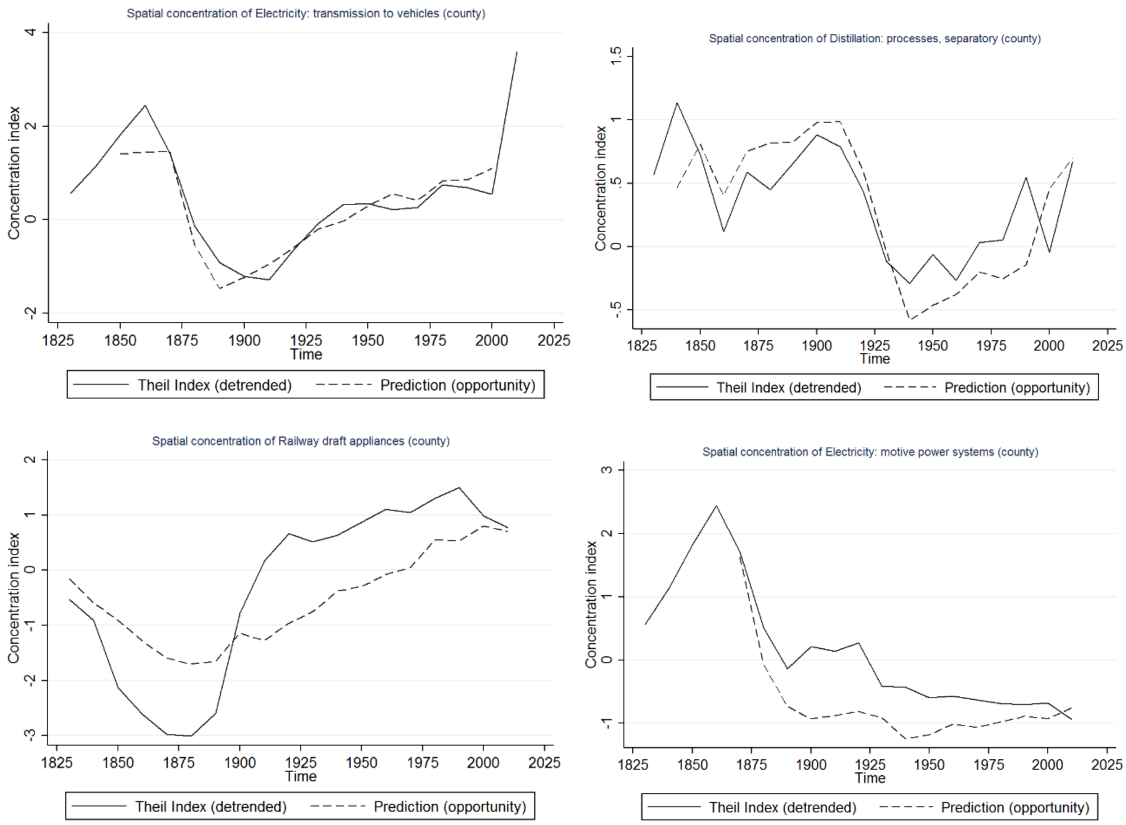
Figure 7, in fact, suggests that: (1) when a technology is growing, innovation becomes more diffused, when a technology is declining, it becomes more concentrated. (2) Entry grows and decline along with the growth of a technology. (3) Regional leaders are increasingly safe as long as a technology is growing, and their position becomes at greater risk when a technology is declining.

As an illustration on how predicting this process is along the life cycle of a technology, we show in Figure 8 how opportunity predicts changes over time in a handful of technological classes. We highlight two points. First, just looking that the de-trended patterns of concentration is further proof that the increase in concentration in the second part of the life cycle is not due to the general trend of concentration at the county level that we observe in the whole economy[4]. Second, each technology has its own pattern, based on its different life cycle. As we saw in Figure 3, for instance, the class "Electricity: motive power systems" is still growing. Consistently, we find and correctly predict a general decline of concentration over time.

Figure 8 - Predictions of concentration based on opportunity



[4] This growth is actually very mild for patents, and only starting from the 80s.



We could begin advancing some hypotheses on why we observe this pattern. Of particular interest is why innovative activities re-concentrate in the second part of the life cycle. Is it just mechanical? There are less patents, so is it that the chances small regions would get one are just smaller? Is this trend thus a simple consequence of scaling laws? Or does it have to do with the inner working of the corresponding industry life cycle? We know that in this phase the industry goes through a shake-out and becomes more concentrated in industrial sense (Klepper, 1996). Do the fewer firms also locate in fewer locations? These are extremely interesting questions that we cannot answer with our data alone. We then leave them to future research.

7 Conclusion

Our work has investigated the spatial patterns of innovation of US metropolitan areas using a long-time perspective. We have used historical patent data to analyse the changing geography of innovation in the US over the period 1836-2010.

Our analysis confirms that technological regimes are strong determinants of spatial patterns of innovation. In particular, we find that *technological opportunities* can predict with extreme precision changes in geographical *concentration*, the *entry* of new regions, and the *stability* of regional leaders. We also find that other two components of a technological regime (i.e. *cumulativeness* and *complexity*) play an important, though smaller role. We instead find, in line with the literature, that *appropriability* is a weak determinant of innovation patterns.

By looking at the long-term dynamics of technological classes we are able to unveil their heterogenous spatial patterns. We show that spatial innovation patterns change according to the stage of development of a technology. For example, growing technological classes, like "electricity", show as expected a long-term trend towards de-concentration. Mature technologies, such as "railway appliances", show instead more complex spatial patterns, from geographical diffusion, during take-off, to concentration during consolidation. The long-run perspective is indeed illuminating as it allows to show that technological regimes do not only differ across technological classes, as the literature as argued so far, but also undergo dramatic shifts within a technology over its life cycle.

One way to see this is to think of the evolution of spatial concentration over time. We know that the US population is getting more concentrated in space, at least at county level (see figure A2). As innovative activities are typically more concentrated than population, one might be justified to hold the prior that concentration of innovation grows over time. Yet, this does not really happen in the aggregate[5] (see Figure 2), and it is blatantly false for individual classes, whose concentration only grows when the classes are declining, while growing classes are deconcentrating.

This might be counterintuitive. Our findings do confirm some expected patterns. For instance, more complex and newer classes are more concentrated. However, when new and complex classes are growing, they would push towards de-concentration. Many questions remain open and are, therefore, fertile ground for future research. For instance, a decomposition analysis could try to understand what is behind the current trends of mild growth in concentration of innovation: is it that oldest technologies are declining? Or is it that so many new and complex categories are appearing?
Another analysis could attempt to link historical patent data to firms and inventors, in order to analyse in greater detail how much the process of geographical de-concentration and re-concentration is related to the life-cycle of the underlying industry. Another avenue of research could focus on role of different types of firms (e.g. incumbents vs newcomers) in the process of regional technological diversification (i.e. spatial entry). More generally, one could use these historical data to investigate the links between spatial and Schumpeterian patterns of innovation.

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[5] There is a mild uptick from the 80s, but the long-run trend from the 40s is that of deconcentration.

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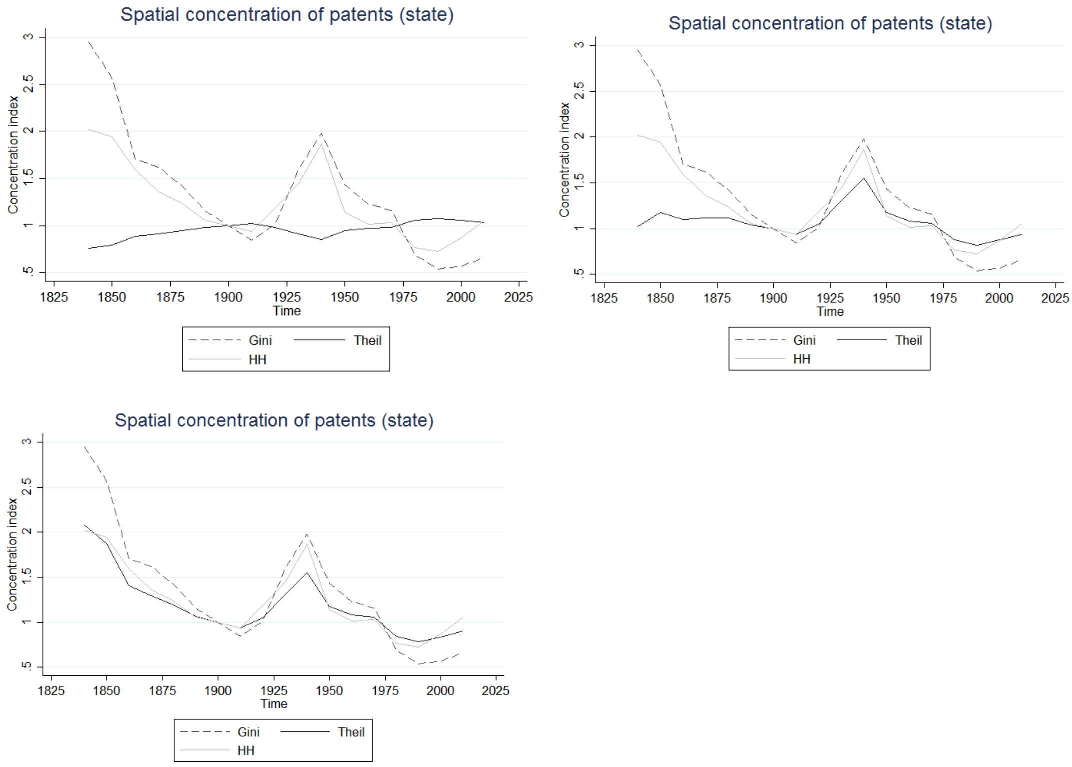
Appendix

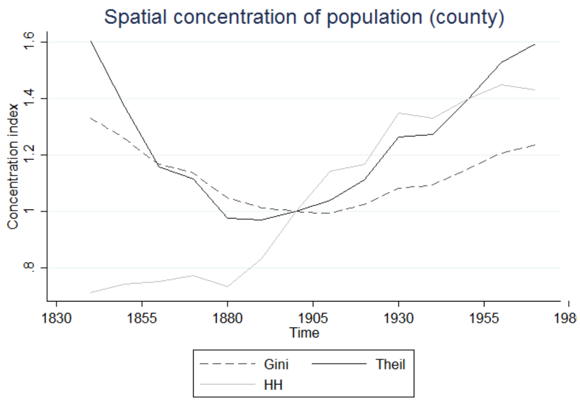
Figure A1 - Measuring concentration



Top row left: correction for changing number of states in both Gini and Theil. Top row right: Gini is corrected for number of states, Theil is not (but it is exponentiated). Bottom row: final measure. Gini is corrected for number of states, Theil for number of states and is exponentiated.

As it can be easily seen, our corrections to keep the number of regions (state in the figure) constant, together with using exp(Theil) rather than Theil, brings all the indicator to agree on the trends.

Figure A2 - Changes in concentration of population



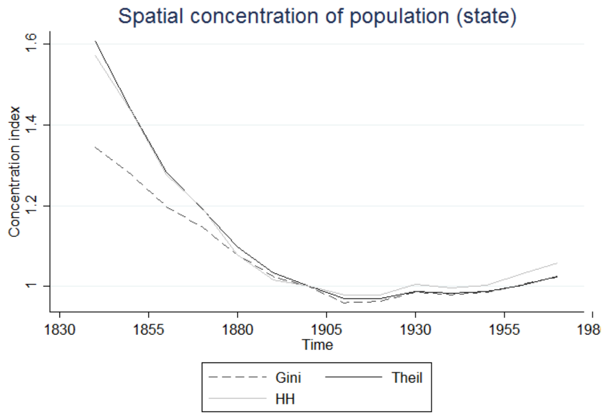
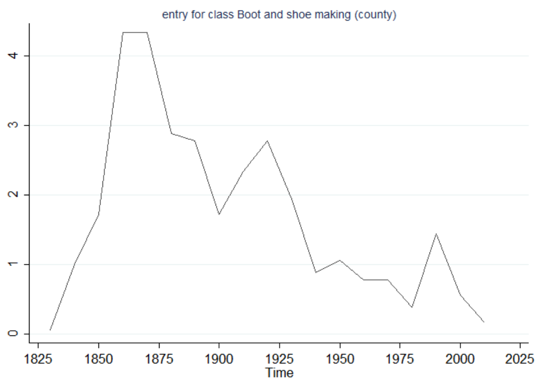


Figure A3 - Stability along the life cycle

We find that stability is positively correlated with opportunity. This translates, longitudinally, to growing stability in the first part of the life cycle and to a decline in the shack-out phase. Figure A3 is an example from technological class `boot and shoe making'

Figure A4 - Entry along the life cycle



As noted in the main text, opportunity positively correlates with entry. This, taken in junction with the dynamics of stability, means that the new regional entry are not sufficient to disrupt the leadership of the major innovators. If anything, it becomes more consolidated during the entry phase.

Table A1 - Fixed-Effect regression

VARIABLES	(1) theil	(2) entry	(3) stability
opportunity	-0.352***	0.619***	0.108***
	(0.0318)	(0.0344)	(0.0134)
approp	-0.0493**	0.0552**	-0.0160
	(0.0224)	(0.0236)	(0.0120)
cumulat	0.0578***	-0.0267	0.0238***
	(0.0158)	(0.0172)	(0.00791)
complex	0.0603	0.181**	-0.0550
	(0.0771)	(0.0833)	(0.0336)
Constant	-2.413***	-0.111	-0.970***
	(0.237)	(0.278)	(0.0986)
Observations	1,262	1,262	1,254
R-squared	0.465	0.694	0.346
Number of c	426	426	422

Robust standard errors in parentheses. All variables in logarithms. Time dummies included
*** p<0.01, ** p<0.05, * p<0.1

Table A2 - First-difference (per decade)

VARIABLES	(1) g_theil	(2) g_entry	(3) g_stability
g_opportunity	-0.367***	0.640***	0.110***
	(0.0378)	(0.0313)	(0.0167)
g_approp	-0.0352*	0.0430*	-0.0179
	(0.0209)	(0.0244)	(0.0113)
g_cumulat	0.0623***	-0.0316**	0.0234***
	(0.0149)	(0.0157)	(0.00776)
g_complex	0.135*	0.148*	-0.0636
	(0.0709)	(0.0801)	(0.0418)
Constant	-0.0236	0.0397**	-0.000464
	(0.0171)	(0.0188)	(0.00753)
Observations	834	834	830
R-squared	0.392	0.685	0.245

Robust standard errors in parentheses. All variable in log-difference. Time dummies included
*** p<0.01, ** p<0.05, * p<0.1

Table A3 - State instead of counties

VARIABLES	(1) theil	(2) entry	(3) stability
opportunity	-0.255***	-0.125***	0.145***
	(0.0104)	(0.0181)	(0.00773)
approp	-0.0802***	-0.0618**	0.0206
	(0.0196)	(0.0273)	(0.0150)
cumulat	0.166***	0.148***	0.00849
	(0.00873)	(0.0198)	(0.00518)
complex	0.106***	0.394***	-0.0183
	(0.0330)	(0.0758)	(0.0156)
Constant	-1.211***	0.942***	-0.815***
	(0.0892)	(0.185)	(0.0603)
Observations	1,262	1,262	1,254

R-squared	0.516	0.094	0.669

Robust standard errors in parentheses. All variables in logarithms. Time dummies included
*** p<0.01, ** p<0.05, * p<0.1

Table A4 - Alternative Concentration indicators

VARIABLES	(1) theil	(2) hh	(3) gini
opportunity	-0.583***	-0.483***	-0.0145***
	(0.0120)	(0.0137)	(0.000428)
approp	-0.0740***	-0.0659***	0.00238***
	(0.0184)	(0.0213)	(0.000581)
cumulat	0.242***	0.292***	0.00720***
	(0.0108)	(0.0136)	(0.000397)
complex	0.164***	0.0336	0.00485***
	(0.0431)	(0.0524)	(0.00145)
Constant	-0.728***	-0.409***	0.0734***
	(0.117)	(0.136)	(0.00358)
Observations	1,262	1,262	1,262
R-squared	0.723	0.537	0.581

Robust standard errors in parentheses. All variables in logarithms. Time dummies included
*** p<0.01, ** p<0.05, * p<0.1

Table A5 – Univariate regressions: Concentration

VARIABLES	(1) theil	(2) theil	(3) theil	(4) theil	(5) theil	(6) theil	(7) theil
opportunity	-0.611***					-0.475***	-0.583***
	(0.00295)					(0.00555)	(0.0120)
approp		-0.176***					-0.0740***
		(0.0315)					(0.0184)
cumulat*			-2.455**			-0.101*	
			(1.045)			(0.0579)	
cumulat				-0.240***			0.242***
				(0.0251)			(0.0108)
complex					0.391***	0.248***	0.164***
					(0.0528)	(0.0237)	(0.0431)
Constant	-0.557***	-4.673***	-1.347***	-4.896***	-1.491***	-1.078***	-0.728***
	(0.0399)	(0.106)	(0.405)	(0.0544)	(0.0783)	(0.0448)	(0.117)
Observations	8,132	1,663	6,185	1,284	7,145	6,185	1,262
R-squared	0.901	0.120	0.351	0.133	0.337	0.729	0.723

Robust standard errors in parentheses All variables in logarithms. Time dummies included.
Column (7) corresponds to column (1) of table 2 (baseline). *** p<0.01, ** p<0.05, * p<0.1

Table A6 – Univariate regressions: Entry

VARIABLES	(1) entry	(2) entry	(3) entry	(4) entry	(5) entry	(6) entry	(7) entry
opportunity	0.641***					0.603***	0.576***
	(0.00291)					(0.00619)	(0.0129)
approp		0.246***					-0.0162
		(0.0314)					(0.0199)
cumulat*			2.884**			-0.0634	
			(1.332)			(0.0771)	
cumulat				0.382***			-0.0645***
				(0.0226)			(0.0122)
complex					-0.248***	0.0362	0.0713*
					(0.0572)	(0.0241)	(0.0420)
Constant	-0.259***	4.463***	-0.778	4.540***	0.144***	-1.336***	0.196*
	(0.0292)	(0.105)	(0.510)	(0.0510)	(0.0340)	(0.0505)	(0.119)
Observations	8,132	1,663	6,185	1,284	7,145	6,185	1,262
R-squared	0.911	0.132	0.340	0.314	0.374	0.808	0.787

Robust standard errors in parentheses. All variables in logarithms. Time dummies included.
Column (7) corresponds to column 2) of table 2 (baseline). *** p<0.01, ** p<0.05, * p<0.1

Table A7 – Univariate regressions: Stability

VARIABLES	(1) stability	(2) stability	(3) stability	(4) stability	(5) stability	(6) stability	(7) stability
opportunity	0.123***					0.103***	0.117***
	(0.00114)					(0.00325)	(0.00433)
approp		0.0697***					0.00803
		(0.00756)					(0.00643)
cumulat*			1.094***			-0.138	
			(0.0974)			(0.0857)	
cumulat				0.125***			0.0427***
				(0.00492)			(0.00370)
complex					0.0694***	0.116***	0.0352***
					(0.0136)	(0.00884)	(0.0122)
Constant	-1.117***	-0.218***	-1.065***	-0.181***	-0.773***	-1.110***	-1.089***
	(0.0145)	(0.0174)	(0.0435)	(0.00926)	(0.0260)	(0.0345)	(0.0406)
Observations	7,000	1,652	6,046	1,265	6,263	6,046	1,254
R-squared	0.725	0.118	0.225	0.507	0.166	0.478	0.765

Robust standard errors in parentheses. All variables in logarithms. Time dummies included.
Column (7) corresponds to column (3) of table 2 (baseline). *** p<0.01, ** p<0.05, * p<0.1