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Papers in Evolutionary Economic Geography

# 24.22

Utrecht University Human Geography and Planning

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June 25, 2024

**Abstract**

While recent studies have heralded large cities as "innovation machines", the majority of regional studies of innovation are based on patent indicators. In this paper, we compare regional patent and innovation counts in Sweden (1970-2014) and document the presence of a sizeable urban bias in patent indicators, which is primarily explained by higher patent filing propensity in urban areas. We also show that using administrative spatial units which do not account for spatial organization of economic activity tends to exacerbate this bias. This poses a problem for academic studies that wish to understand regional innovation, or policy reports benchmarking regional performance.

**Keywords: Regional Innovation, Patents, Urban Scaling, Urban Bias of Patents**

# 1 Introduction

The literature on the geography of innovation activity suggests that innovation is spatially concentrated to large city-regions (Bettencourt et al. 2007b, Broekel et al. 2023, Feldman 1994,

*Josef Taalbi gratefully acknowledges funding support from Sweden's governmental agency for innovation systems, Vinnova (grants no 2014-06045 and 2020-01963).

Feldman & Kogler 2010, Glaeser 2011, Lobo et al. 2013, Ó'hUallicháin 1999), leading researchers to label urban areas as innovation machines, some going as far as to claim that innovation activity does not just take place in cities, but requires them (Florida et al. 2017). Studies have also shown that innovation tends to be considerably more concentrated than population or production activity (Carlino et al. 2007, Ejermo 2009, Florida 2002, 2005, Rodríguez-Pose & Lee 2020, Wojan 2022). Moreover, the spatial concentration of innovation has increased over time (Mewes 2019, Ó'hUallacháin & Leslie 2005, Sonn & Park 2011).

A common explanation circulates around the effect of agglomeration economies (Carlino & Kerr 2015, Duranton & Puga 2004, Puga 2010). More specifically, the literature suggests that large, diversified regions provide better preconditions for innovation by increasing the likelihood of knowledge spillovers (Bettencourt et al. 2008, Gilbert, McDougall & Audretsch 2008). However, given the persistent difficulty in quantifying the impact of knowledge spillovers on innovation activity (Bettencourt et al. 2010), the scope and extent of this urban premium is often debated (Eder 2019, Shearmur et al. 2016).

This problem is further exacerbated by difficulties in measuring regional innovation (Dziallas & Blind 2019, Kleinknecht et al. 2002), which owe to the complexity and heterogeneity of both of the inputs that enter into innovation processes, and the outcomes, viz. the innovation output. A large portion of the empirical literature is based on patent indicators, which are only proxies of innovation activity. Some studies have found patents to be the acceptable measure in the context of regional innovation (Acs et al. 2002), but other studies have suggested that some innovation indicators, such as patents, have an urban bias and that these indicators miss out on non-urban innovation activity (Shearmur 2012, 2017).

In this paper, we analyze regional innovation activity in Swedish regions between 1970 and 2014 with the goal of estimating whether there really is an urban bias for patent indicators. The analysis leverages two sources on regional patenting and a unique literature-based innovation output database for Sweden (Kander et al. 2019, Martynovich & Taalbi 2023). By doing so, we make a fourfold contribution to the literature on regional innovation. First, we develop an analytical framework rooted in the literature on urban scaling of innovation which allows us to decompose the spatial patterns of innovation and patenting activity into several components.

Second, by using this framework we compare regional patent and innovation counts and document the presence of a sizeable urban bias in patent indicators. In other words, we show that using patents as a measure of innovation tends to overemphasize the importance of innovation activity in urban regions. Third, we show that while patents are a good proxy for innovation activity in cross-sections, patents are more questionable for analysis of temporal variation in regional innovation patterns. Finally, we find that the selection of the underlying spatial units plays an important role in analyzing spatial patterns of patenting and innovation activity. More specifically, using administrative spatial units (such as NUTS regions) that do not account for the spatial organisation of economic activity tends to exacerbate the concentration of innovation activity to urban regions in general and urban bias of patent indicators in particular.

The remainder of this study is organized as follows. Section 2 discusses the scaling approach to the study of regional innovation patterns. Section 3 reviews the challenges in measuring regional innovation by discussing strengths and weaknesses of various innovation indicators in the regional context. Section 4 presents an analytical framework for decomposing the scaling of innovation activity across regions into several components, which, among other things, allows to compare the performance of patent indicators to other measures of innovation activity. Section 5 reviews the data and methodology. Section 6 presents the empirical results with respect to (a) spatial concentration of innovation activity, (b) regional scaling of innovation and patenting activity, and (c) performance of various innovation measures in cross-sectional and longitudinal settings. Section 7 concludes.

# 2 Urban scaling: quantifying the geography of innovation

A significant body of literature addresses the topic of geography of innovation activity, with one of the major conclusions that innovation is not equally distributed across regions but is rather spatially concentrated (Feldman 1994, Feldman & Kogler 2010, Glaeser 2011). More specifically, large city-regions have a disproportionately high innovation output by comparison to their more rural counterparts (Bettencourt et al. 2007b, Broekel et al. 2023, Lobo et al. 2013, Ó'hUallicháin 1999), leading researchers as far as to claim that innovation activity does not just take place in cities, but requires them (Florida et al. 2017). Moreover, the spatial concentration of innovation is persistent and, in fact, increases over time (Mewes 2019, Ó'hUallacháin & Leslie 2005, Sonn & Park 2011). A common explanation circulates around the effect of agglomeration economies (Carlino & Kerr 2015, Duranton & Puga 2004, Puga 2010). More specifically, building on the idea of innovation as knowledge recombination (Arthur 2007, Schumpeter 1934) and Jacobs' (1969) description of benefits of diversity in cities for socio-economic interactions, the literature suggests that large, diversified regions provide better preconditions for innovation by increasing the likelihood of knowledge spillovers (Bettencourt et al. 2008, Gilbert, McDougall & Audretsch 2008). However, given the persistent difficulty in quantifying and modelling the impact of knowledge spillovers on innovation activity at the regional level (Bettencourt et al. 2010), the scope and extent of this urban premium is often debated (Eder 2019, Shearmur et al. 2016).

In an attempt to establish empirical regularities in concentration of innovation activity to large city-regions, many empirical studies (Arcaute et al. 2015, Bettencourt et al. 2007a,b, 2010, Broekel et al. 2023, Mewes 2019) have adopted the tool of scaling analysis that allows to model how measurable aggregate characteristics of a system (e.g., regional innovation output) respond to a change in its size (e.g., regional population).

Issues of scaling are deeply involved in the study of systems whose system-level behavior emerges from micro-level interactions between the systems' components (Chave & Levin 2003). In the studies of innovation scaling, regional size is not considered a causal force, but rather an aggregate proxy that embodies diverse socio-economic mechanisms underpinning advantages from the co-location and intense interaction of people. It is in the aggregate of a region that these stochastic processes add up to population size, expressing general effects of agglomeration economies (Bettencourt et al. 2010).

In general, $Y$ obeys a scaling relationship with $N$, when it satisfies (Bettencourt et al. 2007b):

$$Y(t) = Y_0 N(t)^{\beta} \tag{1}$$

where $\beta$ – is the scaling parameter describing three different scaling regimes: (1) $\beta < 1$, a sublinear regime describing the economies of scale, (2) $\beta = 1$, a linear regime, and (3) $\beta > 1$, a superlinear regime associated with increasing returns. Empirical studies show that innovation follows a superlinear scaling relationship, that is, the regional innovation output increases faster than regional population, thus, supporting the notion of concentration of innovation activity to large city-regions. Urban scaling has been shown to encompass not only quantitative (i.e., total number of innovations), but also qualitative aspects of innovation activity: larger cities tend to have higher output of radical (Mewes 2019) and complex innovations (Balland et al. 2020). Earlier studies in the context of the US metropolitan areas found scaling coefficients of about 1.2 to be consistent across various cases and indicators (Batty 2008, Bettencourt et al. 2007a,b, 2008, 2010). More recent studies that explore innovation scaling phenomenon in different countries, while in general confirming the presence of the superlinear relationship between regional innovation output and regional size, find a substantial heterogeneity in the scaling parameter (Broekel et al. 2023, Fritsch & Wyrwich 2021, Lobo et al. 2013).

This research indicates the existence of social mechanisms at play across entire regional systems, which integrate together the complexity of interactions among individuals, households, firms, and institutions living, residing and operating in different regions (Bettencourt et al. 2007b). Scaling relations allow to predict many of the characteristics that a region is expected to assume, on average, as it gains or loses population (Bettencourt et al. 2007a).

In this paper, we address two limitations of the innovation scaling literature that, in our opinion, deserve closer attention. The first limitation is connected to the assumption of scale invariance. In simple terms, scale invariance implies that the difference in innovation output between regions should be independent of regional size ($N$), but dependent on the ratio between regions' sizes. Such systems are often referred to as self-similar (Chave & Levin 2003). This assumption implies that the processes that drive agglomeration and clustering should be similar in cities and regions of any size (Batty 2008) and independent of the selection of underlying spatial units for the analysis. To our best knowledge, only one study to-date (Arcaute et al. 2015) has explicitly tested how various definitions of regions (in their case, by using different minimum population cut-offs for regions to be included in the study) affect the estimated innovation scaling parameter. They demonstrate that the scaling parameter is strikingly different for different population cut-offs, implying the lack of self-similarity for the full range of scales examined. We address this issue by estimating scaling parameters for multiple regional definitions using both administrative and functional spatial units to evaluate the sensitivity of the scaling parameter to the selection of geographical scale.

The second limitation of this literature is that it predominantly examines the relationship between innovation output and regional size only for metropolitan areas and excludes smaller regions and/or rural areas, which does not allow making conclusions about urban premium for innovation activity. This disregards the growing body of literature that shows that innovation can be quite prominent in rural and peripheral regions (Eder 2019, Grillitsch & Nilsson 2015, Shearmur & Doloreux 2022). At the same time, the assumption of scale invariance would imply that the same scaling relationship should apply if peripheral regions were to be included in the analysis. Therefore, following recent efforts by Fritsch & Wyrwich (2021) and Broekel et al. (2023), we investigate the innovation scaling in the whole regional system of Sweden.

A common feature of urban scaling studies is also that they rely heavily on patents as a measure of innovation. This reliance begs the question: how sensitive are estimates of urban scaling coefficients to the choice of innovation indicator?

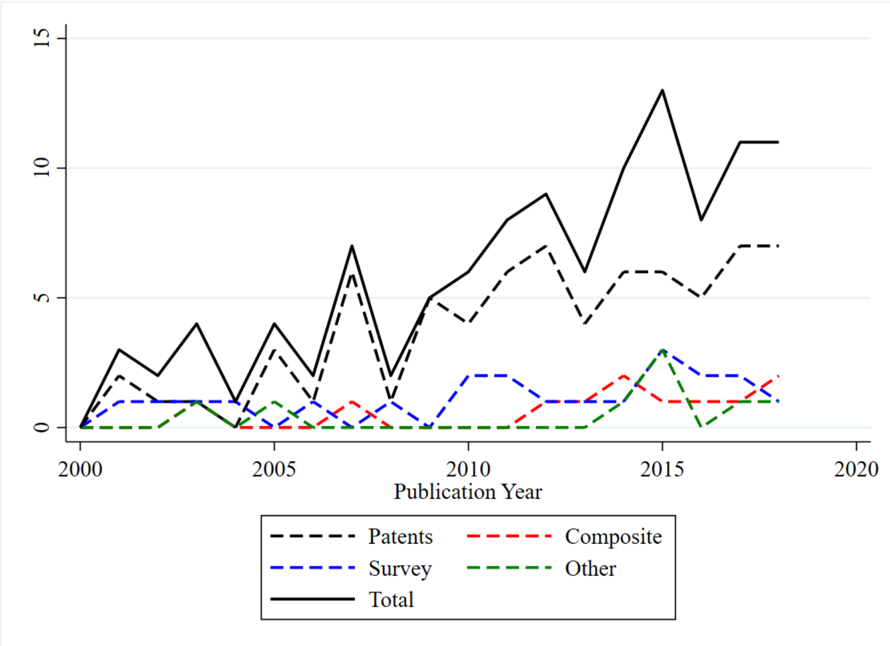
# 3 Measuring regional innovation

There is now a rather extensive methodological literature on different innovation indicators (see e.g., Dziallas & Blind 2019, Kleinknecht et al. 2002, Smith 2004, van der Panne 2007). However, this considerable amount of discussion has not led to a consensus about which indicator(s) should be used for measuring innovation. There are four broad groups of indicators that are used in empirical research on innovation: (1) patents (2) R&D expenditures, (3) composite innovation indices, and (4) direct innovation output measures – innovation surveys and literature-based innovation output (LBIO). In what follows, we will briefly review each of these, focusing specifically on strengths and weaknesses of each type of indicator for measuring the regional innovation output.

## Patents

Patents are by far the most commonly employed indicator of innovation output, both in general and in studies of regional innovation (see Fig. 1)[1].

Figure 1: Empirical studies with "regional innovation" in title, published 2000-2018. Breakdown by innovation output indicator




The basic argument for using patents as a proxy for innovation in regions is that a higher number of patents should result in more innovations in the region (Makkonen & van der Have 2013). Patent data are not only rich in scope and detail, but also widely and readily available for a vast number of countries. Data are also available at the micro-level, making possible analysis for firms, inventors and across regions.

While an attractive measure of innovation output, there are several shortcomings and potential sources of bias, in general, but also for regional innovation studies. One weakness of patents is that not all patented inventions become innovations (Coad & Rao 2008, Gu & Tang 2004), viz. commercialized or otherwise come into economic use (OECD/Eurostat 2019). Patenting may be the outcome of strategic decisions to protect intellectual advances without direct inten-

[1]Fig. 1 shows the results from a search in Web of Science for empirical articles with "regional innovation" in the title and an explicit aim to measure regional innovation output statistically. Patents clearly dominate all articles published between 2000 and 2018. In total, 64% of all papers are exclusively based on patent measures as the innovation output indicator (72 out of 112 articles). A few studies (21 out of 112) used surveys, including Community Innovation Surveys, and a few used composite indicators (11 out of 112). Only one study used a literature-based innovation output (LBIO) methodology.

tion of commercialization (Dernis & Guellec 2001). Hence, many patents are of no or little economic relevance (Brenner & Broekel 2011). The standard way of solving this issue is to use quality-adjusted patents (Hall et al. 2005, Jaffe & Trajtenberg 2002, Trajtenberg 1990), but there is disagreement about to what extent and how patent citations and other quality measures capture economic or other value or actual innovations (Gambardella et al. 2008, Lerner & Seru 2013, Roach & Cohen 2013, Taalbi 2022).

A second drawback is that not all innovations are patented. The empirical literature offers varying figures of patent propensity. Studies for modern samples have found a proportion to patent innovations to lie between 9.6% (Fontana et al. 2013) and roughly 40-49% (Arundel & Kabla 1998, Cohen et al. 2000, Taalbi 2022), depending on whether one counts patents or patent applications. In addition, the patenting propensity varies across sectors (Arundel & Kabla 1998, Makkonen & van der Have 2013, Taalbi 2022). For example, many types of software and service innovations cannot be patented and are therefore not captured by patents (Kleinknecht et al. 2002). By contrast, patents are important means of appropriation in e.g., biotechnology. Moreover, patent counts may arguably be sensitive to changes in legislation and patenting incentives over time and may therefore reflect changes in the patent system rather than trends in innovation activity (Lerner 2009, Moser 2005).

With regards to using patents for measuring regional innovation, concerns have been raised that it is not always clear where firms place their patents (Unger 2000). Also firm-size affects the propensity to patent (Arundel & Kabla 1998). This means that the spatial distribution of large and small firms may affect regional patent counts.

## R & D expenditure

The main argument for using R & D data as a proxy for regional innovation is that an increase in R & D expenditures is expected to result in higher innovation output of a region (Makkonen & van der Have 2013). The main advantage of using R & D data as an innovation indicator is that it is, by far, the longest-standing area of data collection on innovation activity, with detailed classifications available and a good harmonization across different countries (Smith 2004).

The limitations of R & D statistics stem mainly from the fact that R & D does not necessarily correspond to innovation per se, but only informs about the resources systematically devoted to find new innovations (Gu & Tang 2004, Nelson 2009). In that, R & D is but one of several input factors to innovation process (Kleinknecht et al. 2002, Ratanawaraha & Polenske 2006). Lastly, R & D data tends to underestimate innovation efforts of certain sectors as well as small firms (van der Panne & van Beers 2006).

## Composite innovation indices

Recognizing that innovation is not a single state, but an ongoing process consisting of different phases, it was suggested that input and output measures should be used simultaneously and that their combination will be superior to any single innovation variable (Coad & Rao 2008, Hollenstein 1996). This has resulted in the development of innovation scoreboards and composite indices, such as the Innovation Union Scoreboard (formerly the European Innovation Scoreboard), the Global innovation Index and the Regional Innovation Scoreboard (see e.g., Hollanders & Janz 2013 for an overview).

While these have been argued to capture the heterogeneity of innovation inputs and outputs through summarizing information in several indicators, their validity and suitability for policy making were questioned (Hauser et al. 2018). Indices can produce highly divergent rankings as the construction of indices involves a subjective choice of method and variables, which is also a question of data availability (Makkonen & van der Have 2013). As a result, the number of innovation indices has increased drastically, which reduced their comparability, especially between countries (Lepori et al. 2008) and regions (Archibugi & Coco 2005, Grupp & Mogee 2004, Grupp & Schubert 2010).

## Innovation surveys

Another way to collect data on regional innovation is to survey organizations engaged in innovative activity. The Community Innovation Survey (CIS), executed by national statistical offices throughout the European Union, is an example of this approach. While the collected information is very detailed and covers a wide range of interesting fields on innovation, R & D activities, and collaboration. Moreover, innovation surveys measure directly the output of innovation by asking about new or significantly improved products, services or processes (Smith 2004), which does not apply to previously discussed indicators. In that respect, innovation surveys may offer valuable information about the innovative performance of regions, particularly large city-regions (Makkonen & van der Have 2013).

At the same time, this approach comes with a number of shortcomings: (1) it is not completely objective as firms decide what to consider an innovation (Ratanawaraha & Polenske 2006), (Kleinknecht et al. 2002), (2) technological novelty and economic value of reported innovations can be very heterogeneous (Brenner & Broekel 2011, Makkonen & van der Have 2013), (3) surveys are expensive to produce and the data availability is limited, and (4) surveys suffer from low response rates, which may hamper regional comparisons.

## LBIO

An alternative approach to measuring innovation is the literature-based innovation output (LBIO) indicator, based on the screening of trade journals. Its major advantage is that it captures actual commercialized innovations, while avoiding the self-reporting bias of innovation surveys. Studies based on the LBIO approach cover several countries, including Japan (Greve 2003), Italy (Santarelli & Piergiovanni 1996), Spain (Alegre-Vidal et al. 2004, Villar et al. 2012), the Netherlands (Coombs et al. 1996), the UK (Walker et al. 2002) and the US (Acs & Audretsch 1990, Edwards & Gordon 1984). Nationwide and longitudinal data exists for Finland (Kander et al. 2019, Makkonen & van der Have 2013, Palmberg et al. 1999, Saarinen 2005) and Sweden (e.g., Kander et al. 2019, Martynovich & Taalbi 2023, Sjöö et al. 2014, Taalbi 2017, 2022).

The exact types of materials screened in these studies differ, as some have focused on product announcements (Edwards & Gordon 1984) and others on edited journal materials (Kander et al. 2019), but some common concerns exist. First of all, LBIO captures commercialized innovations (both process and product innovations) to the exclusion of *in-house* process innovations, as the incentives to report or announce in-house process innovations may differ. Just as patenting propensity may differ across sectors, the propensity to report innovations in trade journals may also differ across sectors. Van der Panne (2007), however, did not find a cross-sectoral bias of the LBIO methodology.

Since trade journals report the units that develop the innovations, LBIO data is suitable for studying regional innovation and the spatial distribution of innovation (Kleinknecht et al. 2002, Makkonen & van der Have 2013). A few studies have compared the performance of patents and LBIO as regional innovation indicators (Acs et al. 2002, Gössling & Rutten 2007, Makkonen & van der Have 2013), all of which have found that patents and innovation counts from LBIO databases have moderately high correlation coefficients in cross-sectional data. In particular, Acs et al.'s (2002) seminal and influential study used cross-sectional data for US metropolitan areas, suggesting that patents are "a fairly good, although not perfect, representation of innovative activity". A more recent study by Feldman and Kogler (2010, p. 1080) suggests that inference of geographical innovation activity from patents need to be made with caution. In addition, much of the previous literature has only compared patents and innovation in cross-sectional settings, while concerns remain to what extent patents can be used as proxies in longitudinal settings.

This work is entirely based upon comparing patents with innovation output data based on LBIO. In the next section, we leverage this comparison to develop an analytical framework which allows to decompose the urban scaling of innovation into separate effects that stem from different aspects of regional patenting and innovation.

# 4 Analytical framework for decomposition of urban scaling

Previous studies of regional innovation using patents have typically employed either simple (e.g., Acs et al. 2002, Tavassoli & Carbonara 2014) or quality-adjusted patent counts, viz. weighed by the number of forward citations to patents (e.g., Castaldi et al. 2015, Ejermo 2009). In this study, we compare regional patents to regional innovation output by noting that the population scaling relationship to patent citations can be decomposed and expressed in terms of the crude innovation counts. Let $\text{citations}_r$ be the citations-weighed patent counts in region $r$, and $\text{inno}_r$ the count of (LBIO) innovations. One can then express the citation counts as:

$$\text{citations}_r = \underbrace{\frac{\text{citations}_r}{\text{patents}_r}}_{\text{Citation effect}} \Big/ \underbrace{\frac{\text{comm. patents}_r}{\text{patents}_r}}_{\text{Commercialization rate}} \times \underbrace{\frac{\text{comm. patents}_r}{\text{complexity weighed}_r}}_{\text{Intensive margin effect}}$$
$$\times \underbrace{\frac{\text{complexity weighed}_r}{\text{patented inno}_r}}_{\text{Complexity effect}} \times \underbrace{\frac{\text{patented inno}_r}{\text{inno}_r}}_{\text{Extensive margin effect}} \times \text{inno}_r \tag{2}$$

In other words, it is possible to conceive of five effects that influence the scaling relation of quality-adjusted patents as compared to that of sheer innovation counts. Some of these effects are plausibly biases in the patent indicator. The "extensive margin effect" refers to the extensive margin in the propensity to patent, viz. the fraction of innovations that are patented. Variations across regions in the propensity to patent innovations can be expected if there are different sectoral compositions, or firm strategies and patterns of firm establishment across regions. It is for example known that large multinationals have aggressive patent strategies.

We are also interested in the propensity to patent on the intensive margin. In principle, one could understand this in terms of the average number of patents linked to patented innovations. However, it is useful to differentiate patenting behavior and the patentability of certain technologies, from patenting that results from the complexity of innovations. Therefore, it is useful to differentiate an "intensive margin effect" from a "complexity effect".

To examine the complexity of innovation, this study uses the number of technological classes per innovation (see below). The "complexity effect" is then measured in terms of regional variations in the complexity of innovations per patented innovation. Such variations across regions should reflect differences in industrial structure and technological specialization, but may also more generally be expected to reflect greater complexity in urban environments (Balland et al. 2020, Kuusk & Martynovich 2021).

The "intensive margin effect", resulting from patenting behavior, is the number of patents associated with innovations relative the innovations' complexity. Expressed in other words, the "intensive margin effect" measures the disproportionate use of patents as compared to innovations' complexity. Just as there are differences in the patent propensity at all, it is well known that industries like pharmaceuticals, and large firms and multinationals tend to use patents strategically. One may then expect many more patents, even when adjusting for the complexity of the innovation.

The "commercialization rate" expresses the regional variation in the propensity to file patents relative to the propensity to commercialize patented technologies. If the analytical interest is to capture innovation activity, systematic variations across regions in this regard should be understood as a measurement bias. One should note that a higher "commercialization rate" effect will decrease the overall urban scaling, since it means that urban (populated) regions have a higher propensity to commercialize patents, reflecting a closer connection between patents and actual innovation activity.

Finally, the "citations effect" expresses variations in citations per patent. Although the extent to which patent quality measures capture economic value or significance in general have been called into question (Abrams et al. 2018, Criscuolo & Verspagen 2008, Higham et al. 2021, Taalbi 2022), there are no strong reasons to doubt that regional variations in citations per patent should express knowledge flows and the concentration of influential patents in that regard (Jaffe & Trajtenberg 2002).

All this serves as a useful conceptual device, enabling an understanding of the relations between different measures of innovation activity. Recall the scaling relationship for citation counts $\text{citations}_r = N_r^{\beta}$ where $N$ is population in a region. Re-expressed in terms of the population scaling relationship, one can obtain:

$$\ln \text{citations}_r = \beta \ln N_r = (\beta_{ce} - \beta_{cr} + \beta_{ime} + \beta_{comp} + \beta_{eme} + \beta_{inno}) \ln N_r \tag{3}$$

where the subscripts of $\beta$ are shorthand for the citation effect, commercialization rates, intensive margin, complexity, extensive margin effects, and, finally, the scaling relationship to innovation counts, respectively.

# 5 Methods and data

## 5.1 Data

This study employs three data sources: (1) SWINNO (Database of Swedish innovations), (2) patent application counts filed to the European Patent Office (EPO), and (3) patent applications filed to the Swedish patent office.

The main vehicle of analysis of innovation output is SWINNO (Database of Swedish innovations), a database containing over 4,000 Swedish innovations for the period 1970-2014. The underlying approach of the SWINNO database is the above-mentioned LBIO method (Kleinknecht et al. 1993). The data is based on the scanning of fifteen Swedish trade journals, selected to ensure coverage of the manufacturing industry and ICT services (Sjöö et al. 2014). For the period studied here, the source material consists of about 8,600 journal articles containing detailed information about the innovations and firms.

Given the selection of articles, the edited sections of journals were in turn scanned for innovations, defined in SWINNO as an entirely new or significantly improved good, process or service that is commercialised on a market. Only innovations developed by Swedish companies were covered, in part because the editorial mission of the trade journals is more or less confined to the Swedish industry.

The geographical data on innovation output used in this study refers to the place where the innovation was developed. Through a series of steps, 96% of all innovations could be linked to a geographic location with a stable coverage over time. The first step was to read innovation biographies contained in the trade journal articles. For those that could not be geocoded using this data source, other sources company histories and information about active persons were used (see also Martynovich & Taalbi 2023 for a brief discussion).

The patent counts filed to EPO were collected from the REGPAT database (Maraut et al. 2008) and matched to municipality codes using the applicant inventors' address. It is possible to both use the sheer counts of patents that have at least one inventor living in a region, but also to weigh the patents by the number of inventors, such a patent is counted only once. We focus on sheer innovation counts but also compare with inventor-weighted counts (Table 1).

As a control, patent applications filed to the Swedish patent office (www.prv.se) were also used. The data on patent applications filed to the Swedish patent office were collected through manual searches, using the applicant inventors' geographical location. The national data differs from the EPO data in a few respects. Firstly, it is clear that patent applications to the national patent office are more often incremental inventions, while applications to the EPO are believed to reflect higher degrees of novelty on average. A practical difference is that, unlike EPO patents, it was not possible to weigh patents by inventor, so the regional patent measure counts the number of times a patent is filed by an inventor located in a region (Table 1). Thirdly, since the patent database is not available in aggregate form, patents were matched to municipalities by using Swedish population centers (Swedish "tätorter"), defined by Statistics Sweden as areas with at least 200 inhabitants, as the search criteria. Each patent was then linked to its municipality. This means that smaller villages with less than 200 inhabitants were not included. The population living in smaller villages with less than 200 inhabitants has amounted stably to 3% since the early 2000s. Hence, statistics on patents filed to the Swedish national office may slightly exaggerate the concentration, but may be expected to be a good enough representation of the national patenting patterns for our purposes. In practice, as will be seen below, patents filed to the Swedish national office has a less urban profile than EPO patents, despite being marginally biased in the other direction from the way the data was collected.

## 5.2 Patenting, innovation and urban scaling

This study uses the three above-mentioned measures as basic sources of information on patent and innovation activity. However, regional patenting and innovation activity can be measured in different ways. Table 1 summarizes the different variables construed to account for regional variations in innovation activity.

To operationalize the analytical framework presented in section 4 and equation 2, the current study uses sheer regional innovation counts as a baseline. A second variable counts the number of innovations that had a EPO patent application, matched through Google Patents (Johansson et al. 2022, Taalbi 2022). A third variable measures complexity. To examine the effect of the complexity of innovation, this study also uses the number of technological classes

Table 1: Main measures of innovation and patents.

| Variable | Description | Source |
|---|---|---|
| Innovation count | Count of significant innovations developed in region $r$ | Martynovich & Taalbi (2023) |
| Patented innovations | Count of innovations developed in region $r$ that had at least one EPO patent. | Johansson et al. (2022), Taalbi (2022) |
| Complexity weighed | Count of innovations developed in region $r$ that had at least one EPO patent, weighed by the number of unique IPC 4-digit classes in all patents associated with the innovation. | Johansson et al. (2022), Taalbi (2022) |
| Patents with innovation link | Count of EPO patents linked to a SWINNO innovation developed in region $r$ | Johansson et al. (2022), Taalbi (2022) |
| Swedish patents | Count of patents filed to the Swedish patent office having an inventor living in region $r$. | www.prv.se |
| EPO | Count of patents filed to EPO having at least one inventor living in region $r$ | REGPAT |
| EPO, inventor weighed | Count of patents filed to EPO, weighed by number of inventors | REGPAT |
| EPO, citations | Count of forward citations for EPO patent applications | REGPAT |

per innovation (compare e.g., Corrocher et al. 2021, Lerner 1994, Squicciarini et al. 2013). These measures of complexity are constructed through the *patent scope*, defined in terms of the number of distinct 4-digit subclasses of the International Patent Classification (8th edition) (Squicciarini et al. 2013) listed in the patent document. To construct a complexity variable on the level of innovations, which may be linked to several patents, this study uses the total number of unique IPC 4-digit subclasses of an innovation (Johansson et al., 2021). Formally, if an innovation $i$ has a set of patents $p(i)$ with IPC classes $IPC_{p(i)} \in 1, \ldots, N$ the total number of unique IPC digits is $C_i = | \cup_p IPC_{p(i)}|$. To control the sensitivity of the results, we also ran separate regressions for an alternative measure which is the maximum patent scope of all EPO patents associated with an innovation, calculated by taking the maximum $C_i = \max |IPC_{p(i)}|$. These results did not produce substantial differences, and we therefore focus on the first measure in presenting the results.

A fourth variable counts the number of patents associated with an innovation (Taalbi 2022). These variables are compared with the patent indicators: the count of Swedish patents and EPO patents with an inventor based in a region, the inventor-weighed count of EPO patents, and the citation-weighed count of EPO patents.

## 5.3 Spatial units and additional variables

Initially, the geocoding of innovations in all three data sources is performed at the municipality level. Thus, one of the spatial units in our analysis is a municipality (Swedish: *kommun*). To investigate whether scaling relationship is sensitive to the selection of a spatial unit, we aggregate the innovation output to NUTS3 level, which in Swedish case corresponds to a county (Swedish: *län*). This is valuable since NUTS regions are commonly used in studies on regional innovation (which should improve the comparability of our results) and are also used for implementation of policy. Finally, apart from two administrative spatial units, we aggregate innovation output to the level of local labour markets (LLMs). The motivation is that knowledge flows in Sweden have been demonstrated to transcend municipal borders while being bounded within functional regions (Andersson & Karlsson 2007). In that respect, these units are supposed to better capture the organisation of economic activity in space.

Temporally, we structure our observations into 9 periods: $t \in \{1970-1974, 1975-1979, \ldots 2010-2014\}$ . Using five-year periods is preferred as our main interest lies in understanding regional patterns over the long-term, while yearly innovation and patent counts can be volatile.

Data for Swedish patents and innovations are available for the entire period 1970-2014. EPO was established in 1977. For this reason, while we use all available data for descriptive analysis, we restrict our regressions to the five-year periods 1980-1984 to 2010-2014.

Population data in this study comes from Statistics Sweden. This study uses regional population data for the period average (e.g., the average yearly population of 1970-1974).

Summary statistics for all variables used in this study are found in Table 2.

Table 2: Summary statistics

| Variable | Municipalities | | | NUTS3 | | | LLM | | |
|---|---|---|---|---|---|---|---|---|---|
| **Variable** | **Mean** | **Std. Dev.** | **N** | Mean | Std. Dev | N | Mean | Std. Dev | N |
| Patents (SE) | 39.523 | 99.585 | 1953 | 525.095 | 750.767 | 147 | 108.108 | 366.305 | 714 |
| Innovations | 1.57 | 5.361 | 1953 | 20.864 | 27.971 | 147 | 4.296 | 13.576 | 714 |
| Pat. innovations | 0.735 | 2.788 | 1953 | 9.769 | 13.692 | 147 | 2.011 | 6.667 | 714 |
| Complexity weighed | 7.873 | 48.874 | 1953 | 104.592 | 203.469 | 147 | 21.534 | 96.17 | 714 |
| Inno. patents | 4.739 | 52.53 | 1953 | 62.959 | 266.785 | 147 | 12.962 | 121.596 | 714 |
| Patents (EPO) | 35.941 | 271.176 | 1953 | 477.503 | 1259.348 | 147 | 98.31 | 586.631 | 714 |
| Inventors (EPO, weighted) | 33.899 | 125.026 | 1953 | 450.367 | 886.259 | 147 | 92.723 | 415.456 | 714 |
| Population | 31464.576 | 57360.168 | 1953 | 418029.361 | 439927.393 | 147 | 86064.868 | 221041.174 | 714 |

# 6 Results

Section 6.1 presents the descriptive evidence for concentration of innovation and patent activity across Swedish regions. Section 6.2 presents the result of estimation of scaling parameters using various innovation output indicators as well as different spatial units. Finally, section 6.3 asks to what extent the different measures capture similar information in general and whether patents can predict innovation outcomes in cross-section and longitudinal settings (compare Acs et al. 2002).

## 6.1 Concentration of innovation activity

To investigate the spatial patterns of concentration of patenting and innovation activity, we calculate four measures of regional concentration. For simplicity of exposition, the analysis is carried out for local labour markets (the results for other spatial units resemble the patterns specified below).

The simplest concentration measure is the share of innovations or patents developed in metropolitan regions (Stockholm, Gothenburg, and Malmö) in the total innovation output of Sweden.

The second measure is Hirschman-Herfindahl index $HHI_t$, calculated as

$$HHI_t = \sum_i s_{it}^2 \tag{4}$$

where $s_{rt}$ is the share of innovations or patents of region $r \in 1, 2, ..., R$ in period $t$.[2]

A third measure is entropy given by

$$H_t = -\sum_{r=1}^{R} s_{it} \log(s_{it}) \tag{5}$$

where $s_{it}$ is as above, the share of innovations or patents of a region $r \in 1, 2, ..., R$ in period $t$ (Theil 1972). The entropy measure is inversely related to concentration, that is lower values of entropy indicate higher concentration.

[2]Since in our case there is a fixed number of regions, there is no need for normalization of the Hirschman-Herfindahl index.

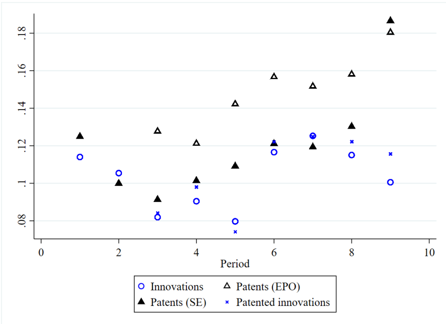
Finally, we calculate the Gini coefficient which indicates whether innovations or patents are skewed towards populated areas. It is calculated as

$$G_t = 1 - \sum_{k=1}^{K} (N_{kt} - N_{k-1t})(Y_{kt} + Y_{k-1t}) \tag{6}$$

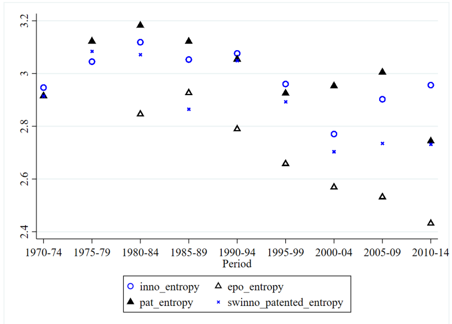
where $N_k$ is the cumulated proportion of the population variable, $Y_k$ is the cumulative proportion of innovations (or patents) and $k \in \{0, 1, ..., K\}$ is an index of regions in order from the region with smallest to the largest share of innovations (or patents). The results of calulating the four concenration measures are presented in Figure 2.

Figure 2: Concentration measures for patent and innovation counts

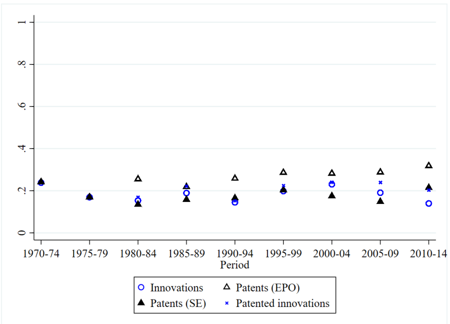
(a) Hirschman-Herfindahl index



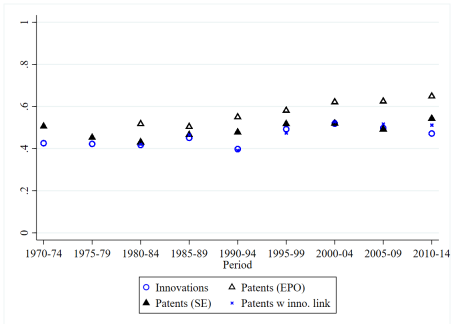

(b) Entropy




(c) Gini coefficient




(d) Share of metropolitan areas (Stockholm, Malmö, Gothenburg)



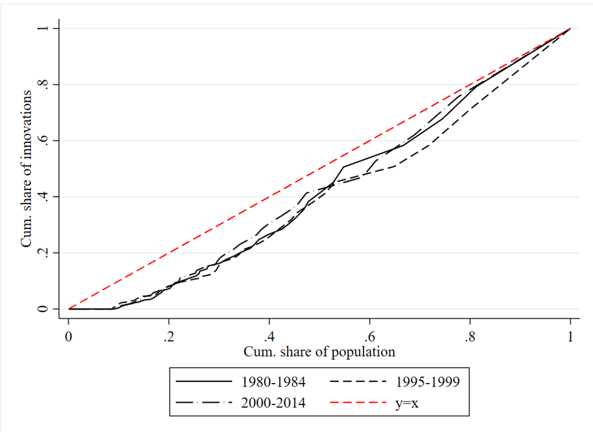

An expected result apparent from Figure 2 is that innovation and patenting activity is concentrated to metropolitan areas (see panel (d)). All four indicators also point to a pronounced increase in concentration over the observed time period. This concentration is more obvious in the share of innovations or patents occuring in metropolitan areas, as well as HHI and entropy measures. The Gini coefficient suggests an overall increase in concentration (or inequality) mainly between the 1980s and late 1990s, but is less clear overall. This points to the fact that

Gini coefficient accounts for the redistribution of population towards metropolitan areas during the observed time period.

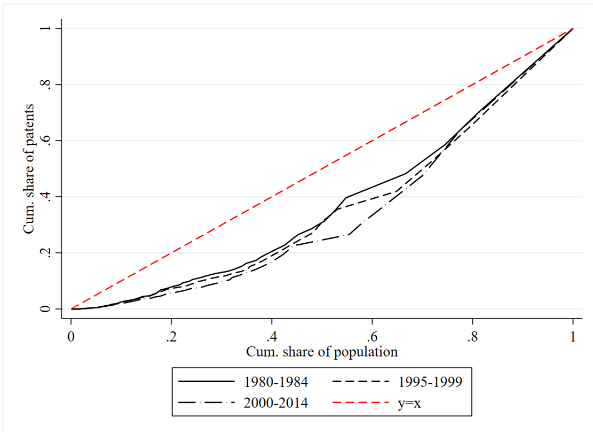
An interesting pattern emerges when considering different innovation measures. Consistently across all measures of concentration, EPO patents tend to stand out as most concentrated (in comparison to innovation and patents filed to the Swedish office. This result can further qualified by looking at the Lorenz distribution curves in Figure 3. They suggest significant differences between innovation output and patents to the national office, on the one hand, and patents filed to the EPO, on the other. Roughly half of all innovations were made in regions accounting 60% of the population, and roughly half of all patents filed to the Swedish patent office were made in regions with 60% of the population. Conversely, below 40% of all EPO patents, were made in regions with 60% of the population.

Figure 3: Lorenz curves. The Gini coefficient is equivalent to the area under the Lorenz curves divided by the area under the equality curve $y = x$.

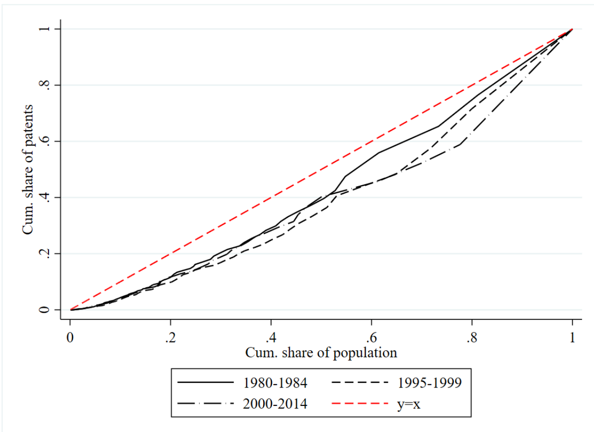
(a) Innovation output




(b) Patents (EPO)




(c) Patents (SE)



In sum, the descriptive evidence unanimously suggests that innovation is increasingly concentrated to the metropolitan areas, which falls in line with previous results in the literature (Mewes 2019, Ó'hUallacháin & Leslie 2005, Sonn & Park 2011). At the same time, it appears that the innovation output measure based on the number of EPO patents filed from a region tend to consistently suggest higher concentration of innovation activity that other measure (innovation output and patent filed to Sweden's patent office). This indicates that EPO patents have an urban bias. In the following section, we investigate the extent and sources of this bias in more detail using the analytical framework of scaling analysis.

## 6.2 Urban scaling of innovation activity

To estimate the extent of urban bias in patent indicators, we first conduct standard scaling analysis outlined in section 2. In particular, we follow previous literature (e.g., Bettencourt et al. 2007b) in estimating the scaling coefficient for indicator $Y$ with respect to population $N$ as $Y \propto N^{\beta}$. In particular, we compare scaling coefficients for three different innovation indicators and three types of spatial units.

To estimate the scaling coefficients $\beta$ across these variables, it is necessary to take into account the character of the data. Both innovations and patents are overdispersed count data (see Table 2), and zero-inflated. Using regular OLS requires excluding zero observations and may induce erroneous conclusions (Finance & Cottineau 2019). For this reason, this study uses a negative binomial regression model approach of a regional innovation indicator $y_{rt}$ as

$$Pr(Y = y_{rt}|n_{rt}) = \frac{\mu_{rt}^{y_{rt}} e^{-\mu_{rt}}}{y_{rt}!} \tag{7}$$

where

$$\mu_{rt} = exp(\beta n_{rt} + \nu_{rt}) \tag{8}$$

and $n_{rt,j}$ is regional population expressed in logarithms, and $\nu_{rt}$ is a Gamma distributed random variable. The coefficient $\beta$ then corresponds to the scaling coefficient. The results of estimation are presented in Table 3.

The overall results, presented in Table 3 suggest, first of all, that innovation has an unequivocal urban profile. Irrespective of the choice of innovation indicator and spatial unit, scaling coefficients are significantly above 1, which suggests the superlinear relationship between regional population and regional innovation output. The size of the scaling coefficients, however, varies greatly between 1.139 (for innovations in local labour markets) and 1.760 (for EPO patents in NUTS3 regions). The closer examination of scaling coefficients in Table 3, however, suggests two interesting observations.

First, irrespective of the selection of the innovation output measure, the scaling coefficients are the lowest for local labour markets, while they are higher for administrative spatial units. This goes against the assumption of scale invariance, i.e., that only ratio of region sizes matters for determining the difference in innovation output between them. Rather, our results suggest that selection of the underlying spatial unit may introduce the bias into the relationship between regional size and regional innovation output. In particular, using administrative spatial units tends to produce higher scaling coefficients, which in turn indicates that studies of regional innovation based on administrative regions may tend to overestimate the importance of cities as innovation hotspots. This also has implications for policymaking, as various policy tools (e.g., the European innovation scoreboard) based on administrative units may overemphasize the innovativeness of urban regions in comparison to more peripheral ones.

Second, irrespective of the selection of the spatial unit, scaling coefficients for EPO patents are substantially higher in comparison to innovations and patents filed to Sweden's national office. This suggests that the EPO patents have a pronounced urban bias in that they overestimate regional innovative activity in urban regions as compared to more peripheral ones. This is particularly obvious at the level of NUTS regions which are commonly used for studies of regional innovation in the European context.

In order to understand from where this systematic difference between EPO patents and innovation counts stems from, we use the decomposition framework outlined in section 5.2. We present the full set of scaling coefficients for different specifications of spatial units in Figure 4. Robustness checks based on employment are available in Supplementary Information (Figure S1).

Table 3: Scaling of innovation and patents (municipalities, local labor markets and NUTS 3 regions)

| | Innovations | | | Patents (SE) | | | Patents (EPO) | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| | Mun. | LLM | NUTS3 | Mun. | LLM | NUTS3 | Mun. | LLM | NUTS3 |
| main | | | | | | | | | |
| Pop. (log) | 1.327*** | 1.139*** | 1.204*** | 1.232*** | 1.153*** | 1.352*** | 1.427*** | 1.342*** | 1.760*** |
| | (37.16) | (37.24) | (25.45) | (61.05) | (57.24) | (27.92) | (46.98) | (48.80) | (25.31) |
| Constant | 8.012*** | 6.882*** | 6.944*** | 10.68*** | 10.01*** | 10.42*** | 10.28*** | 9.350*** | 10.30*** |
| | (37.23) | (39.72) | (39.87) | (82.55) | (77.73) | (57.53) | (52.40) | (52.83) | (39.03) |
| lnalpha | -0.415*** | -1.044*** | -2.284*** | -0.742*** | -0.953*** | -1.971*** | 0.254*** | -0.311*** | -1.238*** |
| | (-4.51) | (-7.26) | (-10.20) | (-20.13) | (-14.75) | (-16.06) | (7.23) | (-4.71) | (-10.48) |
| Observations | 1953 | 714 | 147 | 1953 | 714 | 147 | 1953 | 714 | 147 |

*t* statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The first observation is that the scaling coefficients are much more compressed for local labour markets (functional units) when compared to municipalities and NUTS3 regions (administrative units). This once again suggests that using administrative spatial units that do not account for organisation of economic activity in space tends to overestimate the relative importance of large regions for innovation activity.

Another observation from Figure 4 is that patenting on the extensive margin, viz. the propensity to patent an innovation, does not vary significantly across regions. However, a much more sizeable effect comes from patenting on the intensive margin, even when controlling for differences in complexity of patents. In other words, urban regions tend to file more patents per patented innovation, even when controlling for the complexity of innovations. A counteracting effect stems in most cases from what we have termed the commercialization rate effect, implying that the urban bias of patents is lessened by the urban regions also being more likely to commercialize their patents. Finally, not all spatial levels suggest citation effects when comparing EPO patents with citations-weighted patents, but they tend to be positive.

All in all, earlier studies Bettencourt et al. (2007b) found scaling coefficients of $\beta \sim 1.2$ for patents. Our results suggest that these figures apply for innovation counts and domestic patents, while EPO patents are on the higher side in our estimates. This suggests that EPO patents have a substantial urban bias in the estimates of regional innovative activity.

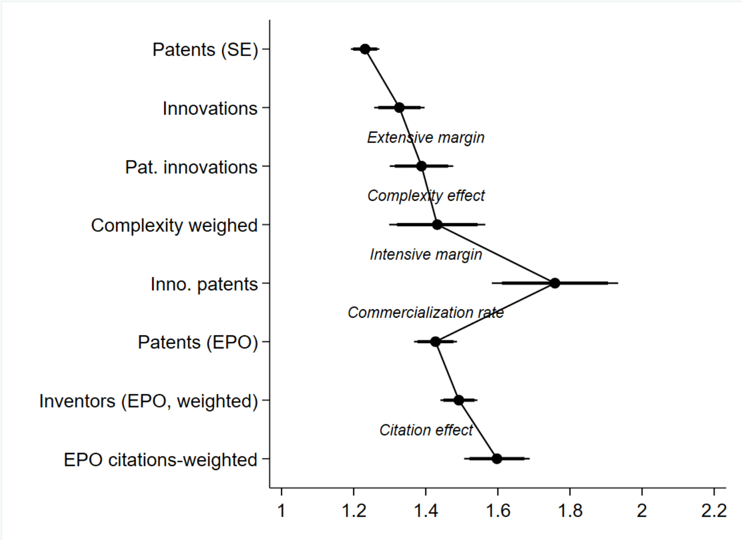
Quite remarkably, most of the differences in the estimated coefficients of sheer EPO counts and innovations can be explained by patenting propensity on the intensive margins, viz. regional differences in patenting behavior. The effect however is counteracted by the negative impact of urban regions also having a greater commercialization rate than other regions, implying that their patents lie closer to innovation counts than elsewhere.

Finally, we show that selection of underlying spatial unit tends to impact the scaling coefficients. In particular, using administrative spatial units that do not account for the spatial organization of economic activity tends to exacerbate the urban bias of all innovation indicators.

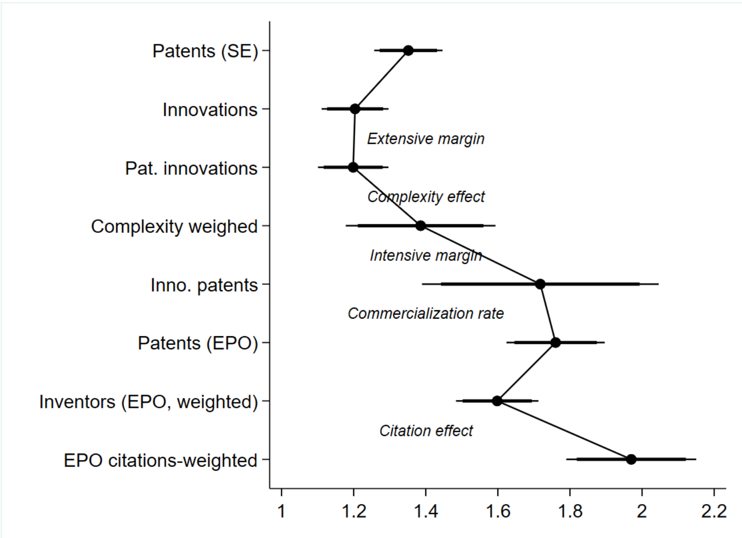
In that respect, our results suggest that using the distribution of patents over NUTS regions which is the backbone of many studies of regional innovative activity in European regions (both

Figure 4: Scaling coefficients for measures of inventive and innovation activity. Municipalities (a), NUTS3 regions (b), and local labor markets (c).

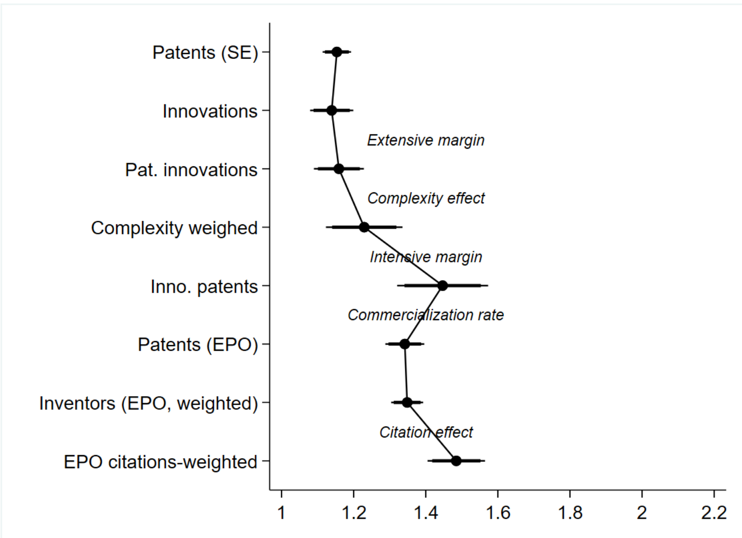
(a)




(b)




(c)



in single country and multicountry studies) results in dual urban bias, that is, overestimation of the role of large regions and metropolitan areas in innovative activity.

## 6.3 Patents as predictor of innovation output

Given that patent indicators have a clear urban bias as indicated above, the final question that we pose in the paper is to what extent various indicators of regional innovation activity capture similar information in cross-section and longitudinal settings. One may start by noting that basic comparisons of the regional innovation and patent patterns, presented in Figure 5, reveal strong associations between the measures for local labour markets.

At the same time, a closer look at the map of innovation by municipality reveals some noticeable outliers (see Figures 6a-6b). Here, all indicators show a concentration of innovations in municipalities around the big metropolitan areas (Stockholm, Gothenburg, and Malmö). Also, Linköping, Västerås, and Uppsala have relatively many innovations. While patterns seem similar overall, innovation counts from SWINNO appear to capture innovation activity in peripheral areas to a greater extent. This is rather visible in Figures 6a-6b, for example in the northern Sweden. This is possibly a result of SWINNO innovation count measure picking up on small firms and industries that may not have high patenting propensity.

To formally examine the relationship between our innovation output indicator and patents, three different specifications of regression models are estimated. In a first set of specifications (Tables 4-5), we test the association between patent counts and innovation counts, using innovations as independent variable and patents (EPO in Table 4 and patents filed to the Swedish office in Table 5) as independent variables, while controlling for population as well as presence of a university or other higher education establishment.

In Tables 4-5, the first three specifications are pooled regression models where both longitudinal and cross-sectional information is taken into account. In model 1, we estimate a log-log relationship between number of innovations and patents in regions over the whole time period (compare to Figure 5). In these models EPO patents and Swedish patents account for ca 56.8% and 54.7% of variation in innovation counts respectively. This points to a good performance of patent indicators in cross-sectional data.

Figure 5: Innovations and patents, total counts by local labor markets, 1970-2014

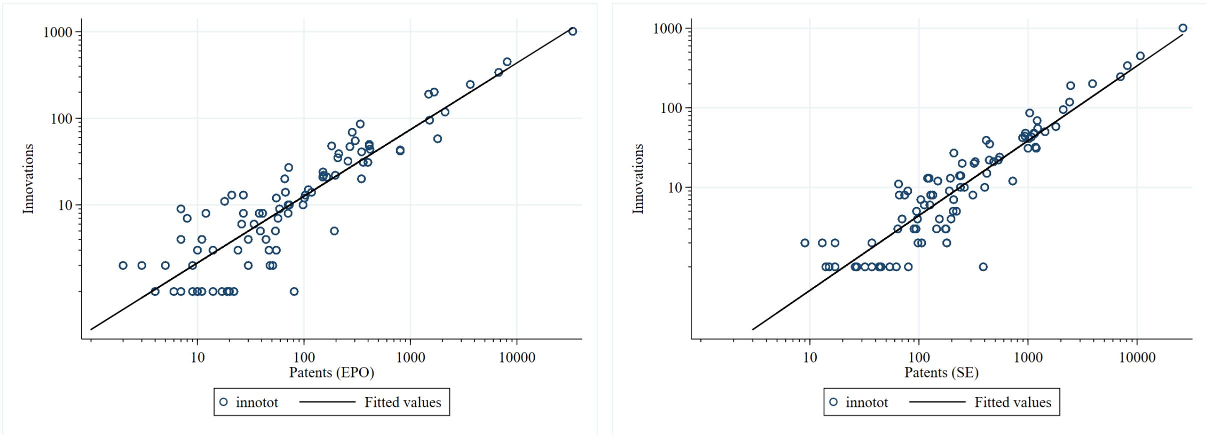



Figure 6: Innovation and patenting counts per municipality, 1970-2014

(a) Innovation counts (b) Patent counts (SE) (c) Patent counts (EPO)

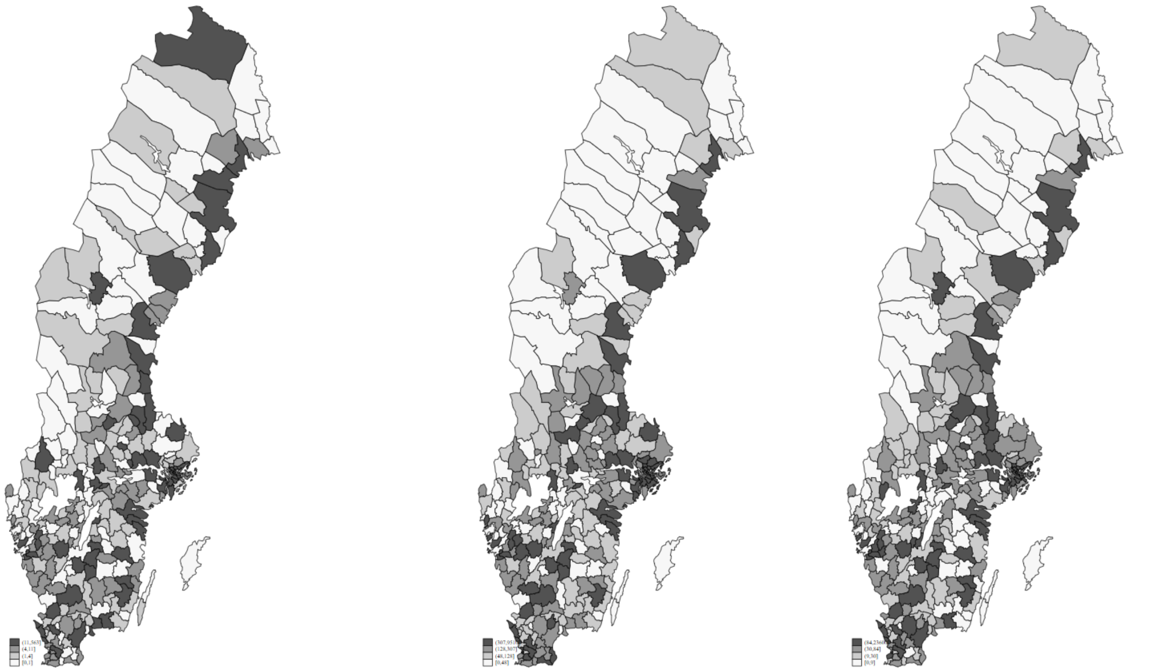


Table 4: EPO patents as predictors of innovations. Five-year periods, 1970-2014. OLS (Model 1 and 4) and negative binomial regressions (Models 2-3 and 5-6).

| VARIABLES | (1) Pooled | (2) Pooled | (3) Pooled | (4) Fixed effects | (5) Fixed effects | (6) Fixed effects |
|---|---|---|---|---|---|---|
| Patents (EPO) (log) | 0.521*** | 0.751*** | 0.332*** | 0.0681 | 0.183*** | 0.100 |
| | (0.0234) | (0.0235) | (0.0457) | (0.0713) | (0.0620) | (0.0616) |
| Population (log) | | | 0.663*** | | | 1.246** |
| | | | (0.0683) | | | (0.542) |
| Constant | -0.519*** | -1.391*** | 3.196*** | 1.230*** | 3.606*** | 6.214*** |
| | (0.0757) | (0.0998) | (0.475) | (0.205) | (0.493) | (1.204) |
| Year dummies | NO | NO | NO | YES | YES | YES |
| Observations | 373 | 604 | 604 | 366 | 597 | 597 |
| R-squared | 0.596 | | | 0.107 | | |
| Pseudo R2 | | 0.235 | 0.264 | | 0.403 | 0.406 |
| Log-likelihood | | -1094 | -1051 | | -828.4 | -824.3 |

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

Table 5: OLS and negative binomial regressions. Swedish patents as predictors of innovation counts. Five-year periods, 1970-2014

| VARIABLES | (1) Pooled | (2) Pooled | (3) Pooled | (4) Fixed effects | (5) Fixed effects | (6) Fixed effects |
|---|---|---|---|---|---|---|
| Patents (SE) (log) | 0.590*** | 0.919*** | 0.476*** | 0.173** | 0.161** | 0.0932 |
| | (0.0254) | (0.0235) | (0.0492) | (0.0704) | (0.0732) | (0.0768) |
| Population (log) | | | 0.587*** | | | 1.352*** |
| | | | (0.0610) | | | (0.497) |
| Constant | -1.164*** | -2.676*** | 1.968*** | 0.503** | 3.387*** | 6.043*** |
| | (0.0993) | (0.113) | (0.484) | (0.238) | (0.546) | (1.125) |
| Year dummies | NO | NO | NO | YES | YES | YES |
| Observations | 491 | 856 | 856 | 482 | 847 | 847 |
| R-squared | 0.604 | | | 0.111 | | |
| Pseudo R2 | | 0.254 | 0.277 | | 0.385 | 0.389 |
| Log-likelihood | | -1434 | -1391 | | -1149 | -1142 |

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

Given that innovation is count data, in models 2 and 3 we estimate the negative binomial models which also suggest a significant relationship between innovation and patent counts. Including control variables, population and municipality dummies, however lowers the coefficients of the patent indicator.

Models 4-6 in control for fixed effects to examine longitudinal variation within municipalities. Patents have a significant effect longitudinally in fixed effects models without the population, but the explanatory power is lower than in the case of pooled models. Also, once we control for population, the coefficient for patent counts is not significant anymore. This result suggests that, while patents are good innovation indicators in cross-sections, temporal trends of innovation activity should not be uncritically inferred from patent data.

It would be possible to be satisfied with this analysis at this point. However, our previous results have shown that both patent counts and innovation counts scale with population. For this reason, correlations in cross-sections may be spatially spurious. A last set of regressions test the association between innovations and patents after controlling for the urban scaling effect. Table 6 presents three specifications of regression models. In a two-step approach (models 1 and 2) we use the residuals from $\log Y_{rt} = \beta_0 + \beta \log N_{rt} + \nu$ (where $Y_{rt}$ is innovation count and $N_{rt}$ is regional population) and using $\nu$ as the dependent variable. Models 3-4 benchmark the innovation indicators by using the share of innovations (or patents) of a region $Y_{rt}/Y_t$ relative to the population share $\dfrac{Y_{rt}/Y_t}{N_{rt}/N_t}$. A third set of model compares innovations per capita with patents per capita in log-log specifications.

The results suggest robust associations between EPO patent applications counts and innovations, but EPO patents only account for 0.1% - 2.5% of the variance in the pooled regressions, and between 3.6%-8.2% when time dummies are included. In other words, when we account explicitly for the scaling of innovation activity with regional size discussed in the previous section, the association between patent and innovation counts is weakened.

All in all, our results follow Acs et al. (2002) in suggesting that patents may be a good measure of innovation activity when sheer counts are considered. However, patents are much less reliable as an indicator when regions of different sizes are to be compared as well as when patterns of innovation activity are analysed in the longitudinal setting.

Table 6: EPO patents as predictor of innovation counts while controlling for population effects in both variables.

| VARIABLES | (1) Two-step | (2) Two-step | (3) Deviations | (4) Deviations | (5) Per capita | (6) Per capita |
|---|---|---|---|---|---|---|
| Patents (EPO) (log) | 0.0647*** | 0.0757*** | | | | |
| | (0.0211) | (0.0209) | | | | |
| EPO (deviations) | | | 0.101 | 0.0963 | | |
| | | | (0.131) | (0.134) | | |
| EPO per capita (log) | | | | | 0.0888** | 0.115*** |
| | | | | | (0.0431) | (0.0439) |
| Constant | -0.249*** | 0.0426 | 2.037*** | 1.492*** | -9.215*** | -8.653*** |
| | (0.0774) | (0.108) | (0.0942) | (0.197) | (0.341) | (0.380) |
| Year dummies | NO | YES | NO | YES | NO | YES |
| Observations | 373 | 373 | 714 | 714 | 373 | 373 |
| R-squared | 0.025 | 0.082 | 0.001 | 0.036 | 0.011 | 0.073 |

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

# 7 Conclusions

This paper has departed from noting several issues surrounding claims about a strong spatial concentration of innovation activity. In this paper, we aimed to critically examine urban scaling of innovation from a number of vantage points, including the measurement of innovation and selection of spatial scale of analysis. To this end we constructed an analytical framework that allows understanding whether patents have an urban bias, and if so, what may explain such a bias.

First of all, our analysis suggests that patent indicators may indeed be at risk of overestimating the concentration of innovation activity to metropolitan areas. In particular, we show that patents filed to the EPO have a consistently different spatial profile than the LBIO-based innovation output indicator as well as patents filed to the Swedish patent office.

This difference is explained by patenting on the intensive margin, viz. the fact that inventors in urban regions tend to file more patents. This holds up even when taking into account difference in the complexity of patents, which may reflect regional industry composition. Our results, in that respect qualify the previous findings in the literature that spatial patenting patterns may reflect the localization of large firms and their patenting behavior (Arundel & Kabla 1998).

Another important finding is that the selection of the underlying spatial units plays an important role in spatial patterns of patent and innovation activity. In particular, we show that using administrative spatial units (such as municipalities and NUTS regions) tends to suggest higher concentration of innovation activity in comparison with functional spatial units that account for spatial organisation of economic activity. This suggests that studies of regional innovation based on administrative regions may tend to overestimate the importance of cities as innovation hotspots. This problem is further exacerbated when these studies use patents as innovation measures. More generally, this implies that studies of spatial patterns of innovation should engage critically with the question of selecting the spatial unit of analysis.

Finally, the third main result is that patents filed to the Swedish or European patent offices have moderately high cross-sectional correlations with the LBIO-based innovation output indicator, but are more questionable predictors of longitudinal patterns in innovation output. This result highlights the fundamentally different dynamics behind patenting and the commercialization of innovations. This is particularly important in the light of the recent call for more historical studies in economic geography (Henning 2019, Martin & Sunley 2022).

Taken together, these results have corollaries for the use of patent data to inform regional policies and research. Patent data are useful regional benchmarks, but should be complemented with other sources when analyzing metropolitan or non-urban patterns and regional performance over time. Since LBIO data or other regional innovation indicators are costly and difficult to assemble, accurately benchmarking innovation is a formidable methodological problem. Our results however offer some lenience. The main watershed in our data is not between patents and LBIO, but rather, a major difference has been between patents filed to the EPO, on the one hand, and, on the other, domestically filed patents and LBIO innovations. This means that, when direct innovation output measures are lacking, different kinds of patent data can and should be used to secure the robustness of results.

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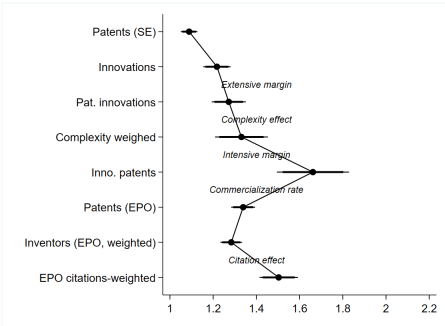
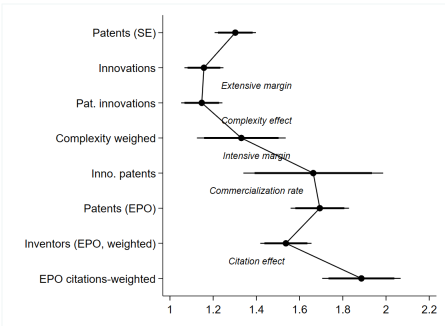
# Supplementary Information

Figure S1: Scaling coefficients for measures of inventive and innovation activity, based on employment rather than population. Municipalities (a), NUTS3 regions (b), and local labor markets (c).

(a)




(b)




(c)