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Abstract

It is widely understood that innovations tend to be concentrated in cities, which is evidenced by innovative output increasing disproportionately with city size. Yet, given the heterogeneity of countries and technologies, few studies explore the relationship between population and innovation numbers. For instance, in the USA, innovative output scaling is substantial and is particularly pronounced for complex technologies. Whether this is a universal pattern of complex technologies and a potential facilitator of scaling, is unknown. Our analysis compared urban scaling in urban areas across 33 countries and 569 technologies. Considerable variation was identified between countries, which is rooted in two fundamental mechanisms (sorting and boosting). The sorting of innovation-intensive technologies is found to drive larger innovation counts among cities. Among most countries, this mechanism contributes to scaling more than city size boosting innovation within specific technologies. While complex technologies are concentrated in large cities and benefit from the advantages of urbanization, their contribution to the urban scaling of innovations is limited.

Keywords: innovation, urban scaling, complexity, patents, sorting, geography of innovation
JEL codes: R12, O33, O18, O57

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1. Introduction

Famously, Florida (2005) argued that the global distribution of innovation is "spiky." Almost twenty years later, this is still very much the case (see Figure 1). Innovation does not randomly concentrate in space, rather, it is seen as an urban phenomenon (Bettencourt et al., 2007; Feldman and Audretsch, 1999; Glaeser, 2011). In particular, the urban scaling literature (Arcaute et al., 2013; Bettencourt et al., 2015, 2010; Bettencourt et al., 2007; Bettencourt and Lobo, 2016; Gomez-Lievano et al., 2017) has sparked discussion on whether an urban premium exists, and researchers have sought to conceptualize and measure it. Empirical analyses have demonstrated that larger cities have a disproportionally higher innovation output by comparison to their rural counterparts, and this relationship is disproportionately large. Nevertheless, the precise sources and extent of this urban premium are still debated (Eder, 2018; Shearmur et al., 2016).

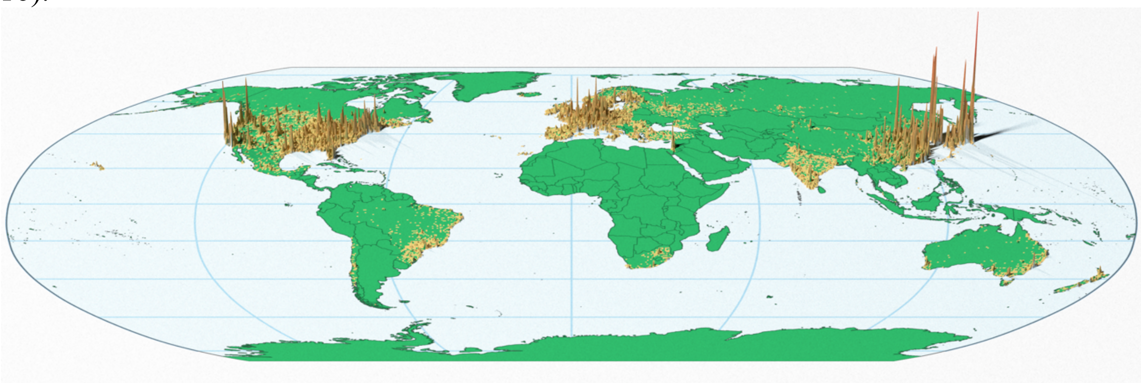

Figure 1: The "spiky world of innovation." Figure inspired by Florida (2005). Spikes represent cumulative sums of patent counts (2001-2014) based on the database of de Rassenfosse, Kozak, and Seliger (2019). The visualization was created using the rayshader package in R (Morgan-Wall, 2023). *A square root transformation was performed for better visibility. A high-resolution version is available for download at: https://www.tombroekel.de/visuals/patents_world_sqrt.png.*

The existing urban scaling literature pays little attention to heterogeneity in scaling across countries and technological fields. It typically claims that empirically identified scaling relationships are universal (Batty, 2008; Bettencourt and West, 2010; Bettencourt et al., 2007; West, 2018). However, the few studies exploring urban scaling of innovation in different countries (Fritsch and Wyrwich, 2021; Lobo et al., 2013), or those looking at specific activities or technologies (Balland et al., 2020; Hong et al., 2020), indicate significant heterogeneity in the relationship between population and inventive output. Specifically, innovations in complex activities are attracted to and facilitated by urban environments (Balland and Rigby, 2017; Balland et al., 2020). However, whether the concentration of complex technologies is also a facilitator of the generalized scaling of innovation is so far unknown.

This paper separates urban scaling in innovation into two core mechanisms: boosting and sorting. Boosting includes the location-based advantages of cities for innovation, which result in larger cities having disproportionately more innovations (per capita) in a specific activity (technology) than their smaller counterparts. That is, as population increases, technological innovation increases more than proportionately. Sorting refers to the urban scaling that originates from the attraction and concentration of innovation-prone activities in cities because the locational benefits of cities are crucial for these technologies. Beyond assessing the magnitude of the two processes in urban scaling, we investigate the extent to which they are related to the concentration of complex technologies in larger cities.

This study merges the recently established patent database (de Rassenfosse et al., 2019) with information on 1,120 functional urban areas (FUAs) in 33 countries. This study thereby adds to the limited literature that has investigated urban scaling internationally, including that of Bettencourt and Lobo (2016); Fritsch and Wyrwich (2021); Lobo et al. (2013).

This study's findings show that urban scaling is a global phenomenon. However, substantial variations exist between countries and technologies. For instance, few technologies receive an innovative boost due to their location in more populous places. The average relationship between city size and technology-specific innovation output is sublinear or not significantly different from a linear one in many countries. Yet, cities do manage to attract more innovation-intensive technologies (sorting), which is identified to be the main source of urban scaling. In line with the literature, this research finds that large cities specialize in more complex technologies and that innovation activities in complex technologies especially benefit from being located in areas with large populations. However, no substantial evidence is found proving that the concentration of complex technologies in larger cities is a driver of the disproportionately large innovation numbers in cities.

The paper is structured as follows: The next section conceptualizes the urban scaling of innovation, including a discussion on sorting, boosting, and complexity. Subsequently, the empirical data and methodological approach are introduced in Section 3. Section 4 describes the empirical results before Section 5 concludes the paper.

2. Theory

2.1. International variations in urban scaling of innovation

Urban areas are perceived as hotspots for knowledge production as innovation activities are disproportionately concentrated there (Bettencourt et al., 2007; Feldman and Audretsch, 1999; Glaeser, 2011). For instance, more than twice the innovations are documented in New York City than in a city half its size. Within the scientific literature, this observation has been termed the "law of urban scaling" (Batty, 2008).

The disproportionate scaling of innovation with population size has been supported by numerous empirical studies (Arcaute et al., 2013; Bettencourt et al., 2010; Bettencourt et al., 2007; Bettencourt and Lobo, 2016; Gomez-Lievano et al., 2017). Recent empirical research also shows that urban scaling is not restricted to innovation in quantitative terms (i.e., the absolute number of innovations), it also encompasses qualitative aspects of innovation: larger cities tend to produce disproportionately more radical (Mewes, 2019) and complex innovations (Balland et al., 2020).

Several researchers claim that the "law of urban scaling" is universal (Batty, 2008; Bettencourt and West, 2010; Bettencourt et al., 2007; West, 2018), which challenges the notion that the historical, physical, political, institutional, sectoral, financial, and cultural specificity of countries and cities significantly shapes their innovation systems and, therefore, their economic performance (Acs et al., 2017; Lundvall, 1992; Nelson, 1993). Crucially, countries differ in the degree of factor mobility (labor and capital) (Bentivogli and Pagano, 1999; Tatsiramos, 2009), which are essential determinants in the concentration of economic activities in space. These cross-cities and cross-country differences in urbanization, factor endowments, and innovation capabilities shape the spatial distribution of innovation activities and could translate into deviations from a global trend.

While the majority of empirical studies argue that a universal scaling law exists, many of them use only data representing the USA (Bettencourt and West, 2010; Bettencourt et al., 2007; Gomez-Lievano et al., 2017; Hong et al., 2020). In contrast, the smaller number of studies exploring urban scaling across different geographic contexts reports substantial international variation (Arcaute et al., 2013; Bettencourt and Lobo, 2016; Fritsch and Wyrwich, 2021; Lobo et al., 2013). Equipped with higher quality empirical data, in particular, through the use of the harmonized global definition of FUAs (Dijkstra, Poelman, & Veneri 2019) and geo-located patents (de Rassenfosse et al., 2019), this study's first aim is to complement existing insights in the cross-country comparison of urban scaling to innovation around the world with a comprehensive analysis. This aim is captured in our first research question:

Research question 1: *To what degree does urban scaling of innovation vary around the world?*

2.2. The two components of urban scaling and their international variation

The theories used to explain urban scaling of innovation are drawn from a wide range of fields and are much more detailed than typical simple empirical approaches. For instance, based on complex systems theory Bettencourt (2013) argues that urban scaling stems from the mixing of populations in cities and their growing infrastructural and social networks. Gomez-Lievano et al. (2017) combine ideas of cultural evolution and economic complexity and develop a theory of urban scaling based on the ability of cities to bring together complementary resources. Unfortunately, capturing these ideas empirically in an international comparison study is nearly impossible. Though, it is possible to improve our understanding of the mechanisms behind urban scaling and the reasons for its variance using empirical methods.

In this study, the three main location-based factors shaping the innovation output of places are translated into two mechanisms (boosting and sorting) that account for the degree of urban scaling of innovation. Especially within the fields of regional science and economic geography the spatial distribution of innovation activities and the role of cities therein have long been the subjects of empirical studies (Feldman and Audretsch, 1999; Rosenthal and Strange, 2001). Brenner and Broekel (2011) review common approaches and summarize them into three fundamental location-based factors:

1. Differences in the ability of places to facilitate local innovation activities.
2. Variations in the number and types of innovation activities present.
3. Spatial heterogeneity in attracting and mobilizing further innovation activities.

Within this paper, the first factor is referred to as *boosting*. Boosting captures all locational characteristics that increase innovation output, and which correlate to (or can be approximated by) population size. Boosting comprises two effects. First, higher degrees of urbanization may stimulate innovation-related efforts. For instance, the higher competitive pressure for scarce resources such as land and human capital in more urban areas (Duranton and Kerr, 2018; Porter, 1998), renders the adoption of technological leadership and innovation-based growth strategies more likely. Consequently, more actors located in urban environments are expected to dedicate resources to innovation activities. Second, innovation-related resources are more productive in densely populated environments translating into higher innovation efficiency. Economies of agglomeration, particularly urbanization and localization externalities, contribute to this. Urbanization externalities lead to easier and cheaper access to local and international markets (Taylor et al., 2002), to a highly skilled workforce (Glaeser and Maré, 2001), to R&D infrastructure (Harrison et al., 1996), to knowledge-intensive business services (KIBS) (Doloreux and Shearmur, 2012) and, spur knowledge spillovers (Greunz, 2004; Henderson et al., 1995). They often coincide with diversification externalities, which originate from the spatial concentration of heterogeneous knowledge and competencies in space allowing for cross-domain knowledge spillovers (Jacobs, 1969; van der Panne and van Beers, 2006). As economic (Youn et al., 2016) and technological diversity (Mewes, 2019) systematically increases with city size, the likelihood of knowledge exchange across different but complementary domains increases accordingly (Gilbert et al., 2008). By contrast, localization externalities, also called *Marshall-Arrow-Romer (MAR)* externalities, emerge from the concentration of the same or similar activities in one location, which allows for efficient labor market pooling, input-output linkages, positive competitive pressure, and intra-industry knowledge spillovers (Rosenthal and Strange, 2001). Even though MAR externalities are not restricted to urban areas, they are more likely to occur in locations of greater size and density. Altogether, the tendency towards more innovation-based strategies and the impact of externalities on innovation productivity, contribute to the same economic activity producing more innovative output per capita when located in larger urban areas, i.e., boosting.

Temporally, the second and third aspects of Brenner and Broekel's (2011) review (variance in existing innovation activities and the attraction of new and additional activities) are closely linked. This is because the potential for places to attract or mobilize specific innovation activities determines the quantities and types of innovation activities present. Within this research, this is referred to as *sorting*. Specifically, this refers to the degree to which larger urban areas systematically accumulate more innovation-intensive technological activities. Note that innovation intensity should not be confused with higher innovation productivity or efficiency. Firms and other organizations performing these activities may simply dedicate more resources (R&D employees, R&D efforts) to innovation processes (Brenner and Broekel, 2011). Ultimately, sorting in the context of urban scaling encompasses all factors that attract above-average innovation-intensive activities to a place that correlates (or can be approximated) with its population size. Most factors that facilitate boosting (e.g., externalities) also shape sorting, making more urban locations more attractive for innovation-intensive activities. However, there are exceptions. For instance, higher resource competition within urban areas can fuel boosting but does not attract further activities.
The second research question conveys the aim to disentangle urban scaling of innovation into sorting and boosting to learn more about its underlying mechanisms.

Research question 2: *What is the magnitude of boosting and sorting in urban scaling of innovation?*

By disentangling scaling into boosting and sorting, a better understanding can be gained of the potential causes of international variation in total scaling, which has been observed in previous studies (Fritsch and Wyrwich, 2021; Lobo et al., 2013).
Both mechanisms are dynamically interrelated, as boosting allows actors in larger urban regions to outcompete and outgrow those in less populous places, which increases the urban concentration of the corresponding activity. In addition, actors in less populace places might decide to move to cities to benefit from their advantages and thereby add to the concentration within cities (sorting) and the advantages cities generate (boosting).
Therefore, given the heterogeneity of factor mobility in countries (Bentivogli and Pagano, 1999; Tatsiramos, 2009), the expectation is that the degree of sorting will vary substantially between countries. And, as countries differ in their average degree of urbanization, infrastructure, institutional structures, and general spatial organization (Hidalgo et al., 2009; United Nations, 2018), cities are unlikely to provide the same boost to innovation activities around the world. Therefore, boosting is also likely to vary across countries. Our third research question summarizes this.

Research question 3: *To what degree do countries differ in terms of sorting and boosting in the context of urban scaling?*

2.3. Complexity and urban scaling of innovation

To illustrate the usefulness of disentangling scaling into sorting and boosting, this research considers a factor that has recently been related to urban scaling of innovation: technological complexity. Research suggests that complex technologies are more likely to emerge in and be attracted to cities (Balland and Rigby, 2017; Balland et al., 2020). Complex technologies combine heterogeneous components in a highly interrelated and structurally diverse manner (Simon, 1962; Zander and Kogut, 1995). Identifying, adapting, and eventually combining these components via collaboration and division of labor is more feasible in larger cities (Balland et al., 2020; Juhász et al., 2021). Consequently, complex technologies can be expected to benefit the most from larger cities (boosting) and thereby contribute strongly to urban scaling. In addition, large cities are more likely to specialize in complex technologies, which, given their higher innovation intensity, should also fuel the sorting effect in urban scaling. The final research question concerns this cluster of ideas.

Research question 4: *Do sorting and boosting systematically vary along the dimension of technological complexity?*

3. Empirical set-up

3.1. Data

To explore the urban scaling of innovation, this research emulates the recent work of Fritsch and Wyrwich (2021). Innovations are approximated using patent applications and functional urban areas (FUAs) (which represent a harmonized delineation of urban areas worldwide) were used as the spatial units of observation. This enabled the construction of a dataset of comparable (urban) areas using a widely accepted measure of innovation.[1]

Although patent applications are by no means a perfect approximation of innovation (see Griliches, 1990, for a detailed discussion), patent data is widely available, is comparable across locations over time, and is thus indispensable for the design of this cross-country study. The patent data prepared by de Rassenfosse, Kozak, and Seliger (2019) was used, which contains more than 18 million patent applications worldwide (including those not granted) until the year 2014. This patent data is not limited to the European Patent Office but includes applications to other patent offices, such as the USPTO and the Japan Patent Office. It also includes information about the patent family, which prevents one from counting the same invention granted to multiple offices twice.

The functional urban areas defined by Dijkstra, Poelman, and Veneri (2019) cover most of the OECD member states. They seek to capture the economic and functional areas of cities. Following the logic of labor market regions, the delineation is based on the daily movements of people, with work-related commuting. The OECD provides geographic shapefiles for 1,199 FUAs in 34 countries[2] (OECD, 2021).

To match patent information with FUAs the exact geo-coordinates (latitude and longitude) were used, as provided in the patent data. These coordinates were based on the address information contained in the patent documents.[3] The geographic information in the OECD shapefiles allows for a straightforward assignment of patents to FUAs. That is, whenever the coordinate assigned to a patent lies within the geographical boundaries of the FUA, it will be assigned to this region. All applications before the year 2001 were excluded because 2001 was the first year with the necessary population data (see below). This left 9,778,948 patent applications from 2001 to 2014. Patents with multiple inventors were counted fractionally (Ejermo and Karlsson, 2006), a method also applied by Fritsch and Wyrwich (2021): for each patent, the share of inventors located in the same FUA was calculated. Hence, in all estimations and figures, “patent counts”

[1] Of course, patents capture inventions rather than innovations. However, this distinction is not essential for the present work, and the more common term “innovation” was used.
[2] The countries and the corresponding numbers of FUAs are listed in Table 6 in the Appendix.
[3] This is different to Fritsch and Wyrwich (2021) who rely on complex global crosswalks to delineate regions. We are confident that our procedure is more accurate.

refer to the sum of patent fractions assigned to FUAs.[4] In total, 7,076,663 patents were assigned to at least one FUA and were consequently allocated according to the fractional counting procedure.

Unfortunately, the 53 functional urban areas of Colombia did not feature any patents listed in de Rassenfosse et al. (2019) and were therefore removed. In addition, 26 FUAs were not linked to patents, leaving a total number of 1,120 FUAs.

The second requisite data set was population information, which was obtained for most regions (995) from OECD Statistics for the years 2001 to 2014. Noticeably, the time series were incomplete for some regions, which was unproblematic for this study's empirical approach as the data and average population size were pooled. For the remaining 125 FUA, the population data for the year 2015 was used, as documented in OECD (2021).

In total, there was complete information (population and patents) for 1,120 regions in 33 countries. This study thereby extended the international representation of the study of Fritsch and Wyrwich (2021) considerably, as their study considered 14 countries only. Almost as many countries were considered as Lobo et al. (2013). More details about the data can be found in the Appendix.

3.2. Technologies and Complexity

To disentangle boosting and sorting as well as assess the potential systematic variance of complexity, this study relied on the technological disaggregation of patents provided by the hierarchical *Cooperative Patent Classification* (CPC). The 4-digit level was used, which offers a useful balance between technological disaggregation and a manageable data structure (Antonelli et al., 2020; Breschi and Lissoni, 2009). This allowed for the distinction of more than 660 technologies. In the technology-specific analyses (see next section), technologies with very low patent numbers were excluded. These were defined as technologies with less than 500 patents.[5] This reduced the number of technologies considered to 569.

The quantification of technological complexity was crucial for the study. Broekel (2019) provides annual estimates of technological complexity for 4-digit CPC classes.[6] The measure of *structural diversity* is based on the representation of technologies as combinatorial networks of interrelated (knowledge) elements. The structure of these combinatorial networks comprised different topologies (e.g., "stars," "lines" and "circles"). Accordingly, technologies were more complex when their combinatorial networks had a greater diversity of such topologies, i.e., more distinct ways in which the technologies' (knowledge) elements were interrelated. Presumably, this increases the effort needed to invent, learn, and copy a technology. The measure of structural diversity captured this diversity at the 4-digit CPC level. Broekel (2019) shows that structural diversity outperforms other measures of technological complexity in mirroring patterns commonly associated with complexity (growing over time, requiring more R&D and collaboration, concentrating in space). Recently, Mewes and Broekel (2022) add to this by showing that this measure of complexity explains the growth differentials of European regions. The technological complexity of the 4-digit CPC technologies was averaged over the period 2001 to 2014, as well.

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[4] The analysis was repeated with a full-counting approach. The results didn't change in a substantive manner. They can be obtained from the authors upon request.

[5] Figure 13 in the Appendix visualizes the distribution of the cumulated numbers of patents across technologies for all countries and the full-time span.

[6] The data is publicly available at https://www.tombroekel.de/updated-values-of-technological-complexity/ and the *GeoInno* package for *R* features a function for the calculation of the *structural diversity* measure, see https://github.com/tombroekel/GeoInno.

3.3. Methodology

Mewes (2019) shows that scaling coefficients change rather slowly over time, which allows for cross-sectional analysis. As already outlined, population and complexity values were averaged across all years, whereas patent numbers were summed to correspond to the total innovative output in that period.

Cross-sectional OLS-regressions were employed relating the logarithm of patent numbers to the logarithm of population. The resulting coefficient of population was interpreted as an indication of the degree of scaling (Bettencourt et al., 2007a). The relationship between population and patents was estimated as reliably as possible (using fixed effects, interaction terms, and clustered standard errors). Still, the results cannot be interpreted causally and suffer from an omitted variable bias, as population is not the primary, let alone, only explanatory factor of patented innovation (Brenner & Broekel 2011). Moreover, patents are not the only or best approximation of innovative output. While this needs to be considered in the interpretation, it is still the most widely used approach in this context.

To answer **research question 1**, the degree to which urban scaling in innovation varies across the world, all country-specific data was pooled, and the OLS was run including country-fixed effects and clustered standard errors at the country level, which provided the baseline model. By estimating varying slopes and varying intercepts models using interactions of country-dummies and population, differences between countries were quantified (Fritsch and Wyrwich 2021).

Research questions 2, 3, and 4 required the disaggregation of scaling into boosting and sorting. According to the discussion, the analysis focused on the technological dimension of sorting. Technologies (4-digit CPC fields) were assumed to represent technologically homogeneous innovation processes, implying that no significant sorting takes place within each technology.[7] That is, if patent numbers per capita within a specific technology were higher in larger regions, it was the result of actors being more innovative there (having a higher innovation efficiency and higher investments into innovation) and not because they operate in technologies that are more innovation-intensive in general. The data was restructured with 569 technology-specific observations for each of the 1,120 regions leading to a total of 637,280 observations. All observations with zero patents were removed, leaving 272,399 valid observations that formed the basis for the subsequent analyses.

To capture the boosting effect, the OLS scaling regression on this data was estimated. This allowed the intercept and scaling-coefficient (slope parameter of population) to vary between technologies.[8] The resulting technology-specific scaling coefficients were not shaped by sorting and hence, represented pure boosting.[9]

Technically, the varying slopes were implemented using a varying-slopes and intercept model (i.e., 569 technology-specific parameters) for population. The technology *B32B (Layered products (products build of strata of flat or non-flat form)* was selected as the reference group because of all technologies, its slope-parameter was closest to 1 (*b=1.000, 95% conf.int: 0.929-1.070, 818 obs.*) when considering country-fixed effects. Using it as a reference allowed for the interpretation of a technology's significant boosting coefficient as over-linear or sub-linear

[7] The relative homogeneity of the presumed innovation processes within 4-digit CPC technologies implied that no substantial sorting of more innovation- and patent-prone subfields correlated with city size. The validity of this assumption increased with further technological disaggregation. Unfortunately, this came at the cost of thinner empirical data. We believe that the 4-digit level represents the best trade-off in this scenario.

[8] Fritsch and Wyrwich (2021) weren't emulated in doing the analysis for patents per inventor. They argue that this ratio represents inventors' productivity, which, in the setting of this research, might capture the boosting effect as well. However, this ratio is heavily shaped by the intensity of collaboration activities and consequently, represents a rather biased estimate of inventor productivity.

[9] All OLS scaling regressions were done using the *fixest* R-package (Bergé, 2018).

scaling with population and consequently, whether there was a significant boosting effect. Hence, these coefficients were referred to as *boosting coefficients* in the following.

In an extension of this approach, variations between countries were assessed with a varying-slopes (i.e., country-specific) model for population using a combination of country and technology dummies. In this case, the technology-country combination "E03C-USA" served as a reference because its slope parameter was closest to 1 (*b=1.00003, 95% conf.int: 0.858- 1.14, 154 obs.*). In consequence, significant coefficients of the varying-slope parameter can be interpreted as indication of slopes that are statistically larger or smaller than 1. To test if international variations significantly shaped the magnitude of boosting, a second-stage analysis was conducted in which the boosting coefficients were regressed on country dummies with the USA set as the benchmark. The USA was chosen because it was the case that was the subject of the most investigation in the scaling literature. As the values of the dependent variable (boosting coefficients) were outcomes of a statistical analysis itself, a meta-regression approach was employed that considers variance in the (statistical) precision with which the values were estimated. This was achieved by employing a residual maximum likelihood approach (REML) in the second stage (Viechtbauer et al., 2015). This two-stage approach also allowed for a simple exploration of the relationship between boosting and complexity, as the complexity of technologies could be added into the meta-regression as an additional explanatory variable.

To isolate the sorting effect from boosting, the degree to which (larger) regions specialize in more innovative (patent-intensive) technologies was assessed. First, each technology's patent intensity was calculated as the average of the ratio between patents and population across regions with at least one patent in the focal technology (INNO_TECH).[10] Second, the technology-specific regional patent numbers (in logs) were regressed onto the corresponding technology's log-transformed patent intensity (the latter being identical across all regions). Figure 2 illustrates this schematically, with the dots representing individual technologies that are sorted according to their patent intensity along the x-axis and their region-specific patent numbers on the y-axis. The slope parameters of the regression obtained represent a simple measure of regions' specialization in innovation-intensive technologies. In practice, we achieve this by pooling all region-specific observations and estimating a varying-slopes and varying-intercepts (i.e., region-specific parameters) model interacting technologies' patent intensities (INNO_TECH) with region dummies (REG). Subsequently, the relationships of these coefficients with population counts were explored with a REML meta-regression, which is illustrated in Figure 3. The region closest to not having any specialization concerning innovation-intensive technologies was chosen as a reference group, i.e., a region with a slope parameter closest to zero. This is region ES048 (Guadalajara, Spain, *b= -0.000352, 95% conf.int: [-0.120, 1.20], 30 obs.*).

[10] The robustness check using the median value of technologies' patent to population ratios yields very similar results.

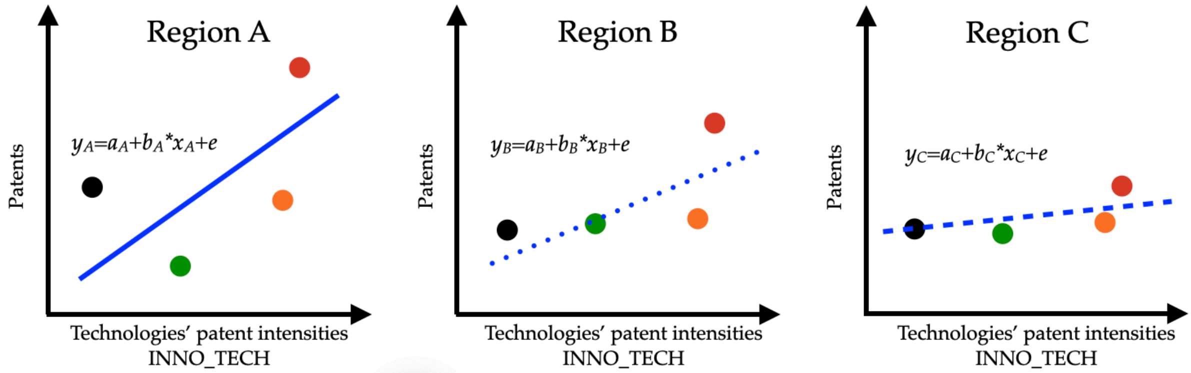

Figure 2: Specialization in innovation intensive technologies

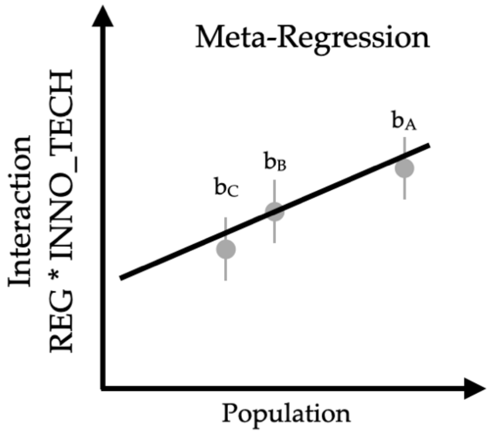

Figure 3: Sorting meta-regression

An interaction of innovation intensity, complexity, and region dummies (INNO_TECH*COMPLEX*REG), provides varying slopes (region-specific) and varying (region-specific) intercepts for the relation of innovation-intensity and complexity. In the second stage, the resulting coefficients were regressed on population to evaluate the relationship between sorting and complexity.

4. Results

4.1. Cross-country differences of urban scaling to innovation

Table 1 shows the results of the typical scaling regression between population and patents (both in logs) across all 1,120 regions. The size of the coefficient for population is relatively large (1.445), but it decreases considerably to 1.269 when considering country-level fixed effects. That the pooled data stems from different sub-populations is also visible in Figure 4. When considering the country-fixed effects the scaling coefficient obtained are very similar to those reported by Bettencourt et al. (2007) and Balland et al. (2020) for USA cities (1.27 and 1.26, respectively). The result without fixed-effects are almost identical to the those reported by Lobo et al. (2013) for the USA and to the one for the combined sample of regions in 33 other countries. The data clearly confirms the existence of positive urban scaling across countries.

	Dep: log (Patents)	
Constant	-12.394*** (-15.878, -8.909)	
log (Population)	1.445***(1.131, 1.759)	1.269***(1.182, 1.355)
FE (Dummies)	No	Countries
Cluster Std. err	Yes	Yes
Observations	1,12	1,12
R^2	0.412	0.878
Adjusted R^2	0.411	0.874
Residual Std. Error	1.928 (df = 1118)	0.891 (df = 1086)
Note:		*p**p***p<0.01

Table 1: Urban scaling in innovation regression

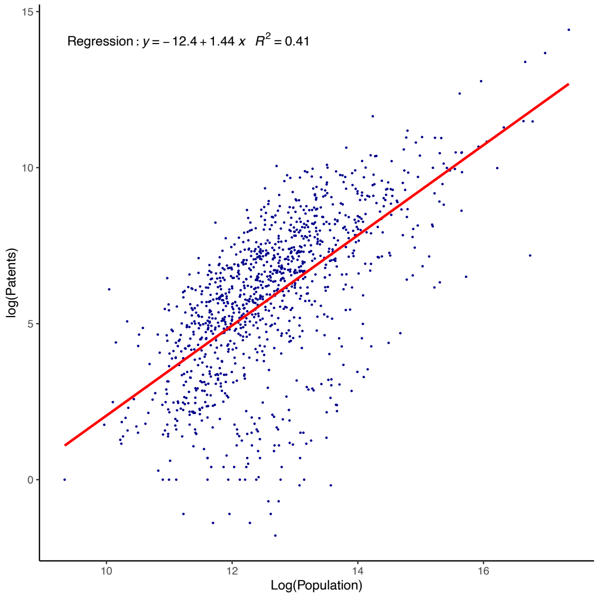

Figure 4: Visualization of urban scaling in innovation

Next, following Fritsch and Wyrwich (2021), the same regression was estimated, this time with varying-slopes (country-specific) for population using the USA as a reference. The slope coefficients are visualized in Figure 5 (Table 8 in the Appendix reports the full regression results). Only 9 out of 30 countries' coefficients are significantly different from that of the USA (at the level of p<0.1). The coefficients are significantly smaller for Switzerland, Ireland, Italy, Lithuania, the Netherlands, and the UK. They are larger for Mexico and Slovenia (there are only two regions in Slovenia). While the signs of the coefficient are the same as reported by Fritsch and Wyrwich (2021), by contrast, the lower scaling for Canada, Germany, and Spain is not observed to be statistically significant in this research. This discrepancy is likely the result of better quality (geo-located) patent data used in this study.

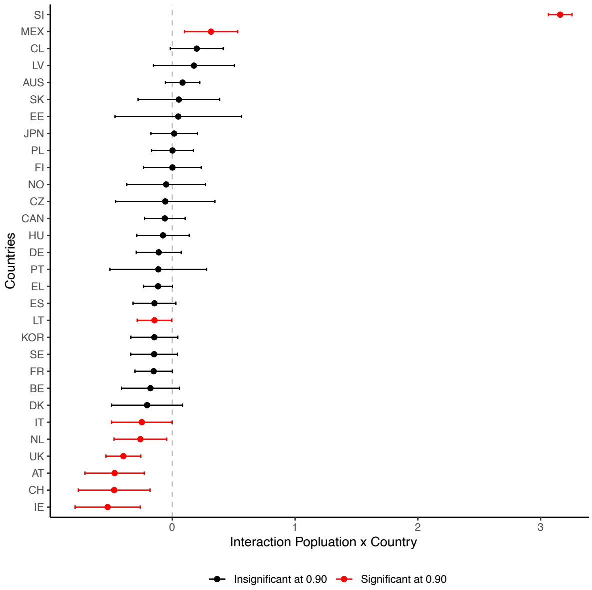

Figure 5: Variations in scaling across countries

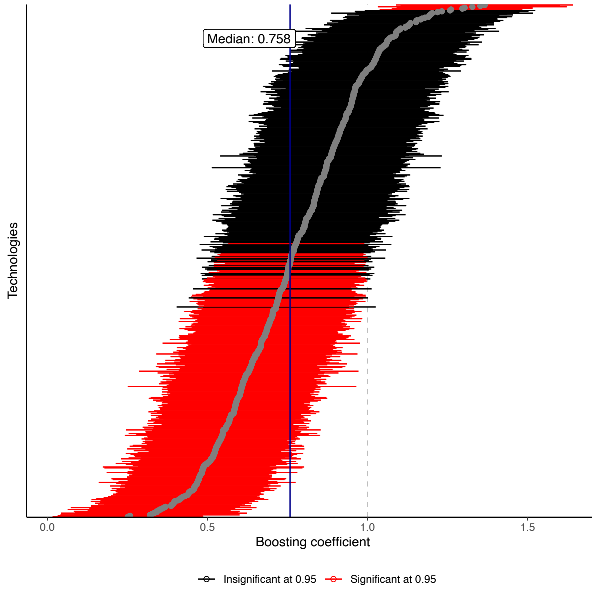

Figure 6: Variations in boosting across technologies

Hence, the analysis provides a mixed answer to the **first research question**: while urban scaling of innovation is observed across all countries and it is not statistically different from that observed in the USA, there are significant differences between some countries. In particular, the UK, Ireland, Switzerland, and Austria show scaling coefficients below one and, accordingly, do not experience superlinear urban scaling of innovation.[11] Consequently, this study casts some doubt on the idea that scaling could hold universally.[12]

4.2. Boosting and sorting in urban scaling to innovation

This study is arguing that scaling is rooted in two effects: boosting and sorting. To identify boosting, the patent data was disaggregated into 569 technology-specific observations and a scaling regression on this basis was estimated whereby the population parameter was allowed to vary between technologies. The resulting coefficients are shown in Figure 6 and the condensed regression results are in Table 9 in the Appendix. Red indicates whether the coefficient is significantly different from the reference technology's slope, which is approximately 1.

The findings are remarkable: across the world, merely four of 569 technologies scale super-linearly, whereas about 50% scale sub-linearly and the remaining technologies scale approximately linearly. That is, in only 4 of 569 cases a larger population leads to disproportionally more patents, and the median coefficient across all technologies of 0.764 is well below 1. This clearly shows that boosting as a part of scaling does not solely account for the superlinear scaling coefficient found in the overall regression.

This is even more interesting given the inter-country variance in boosting. Figure 7 illustrates the results of the varying (country-specific) slopes of technologies (COUNTRY*TECH*Population) in which the boosting coefficients for each country were classified as significantly larger or smaller than 1 or approximately 1 (the summary of the regression results is shown in Table **11** in the Appendix). Most technologies scale approximately linearly or sub-linearly within individual countries. There is only a handful of countries (USA, Germany, Japan, South Korea, France) where larger populations boost the innovation activities of some technologies' (between 21 and 85) super-linearly. Unfortunately, two countries (IS, LU) do not have enough observations to be tested against the reference (USA).

For three countries, most technologies' scale sublinear: Italy, United Kingdom, and Spain. However, there is no apparent reason why boosting differs so much between the observed countries. Both groups of countries feature large cities (in terms of population) and are highly developed. The two groups also simultaneously include highly centralized (France, South Korea, UK) and less centralized (USA, Germany, Italy) countries. The coefficients of the meta-regression, which test if significant differences in boosting exists between countries (using USA as the reference group once again), demonstrate significant inter-country variance (Figure 8 and the according regression results in Table 10). There are only five countries in which the boosting effect is similar to or stronger than that in the USA: Slovenia, South Korea, Japan, Finland, and Germany. Interestingly, the largest boosting is found in countries that are classified as being most economically advanced (Hausmann et al., 2011), an observation which should be explored further in future research.

[11] The coefficient of the USA is 1.362 and the coefficients of these countries' interaction effects are large than its difference to one.

[12] For completeness, we also report country-specific regressions for all countries with at least 20 regions. They are shown in Figure 6 in the Appendix.

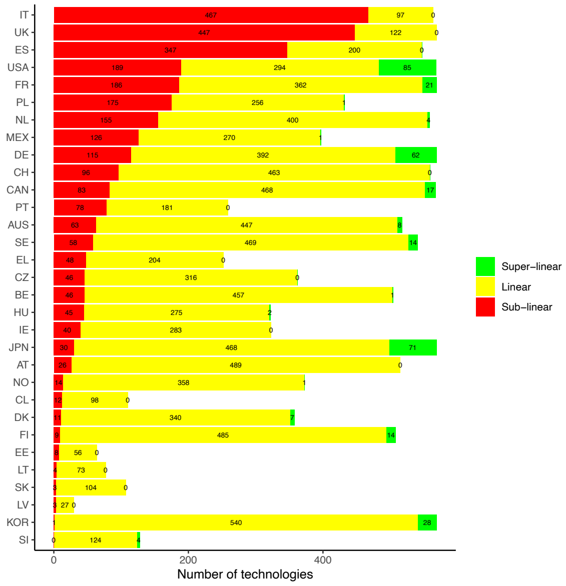

Figure 7: Variations in boosting across technologies and countries

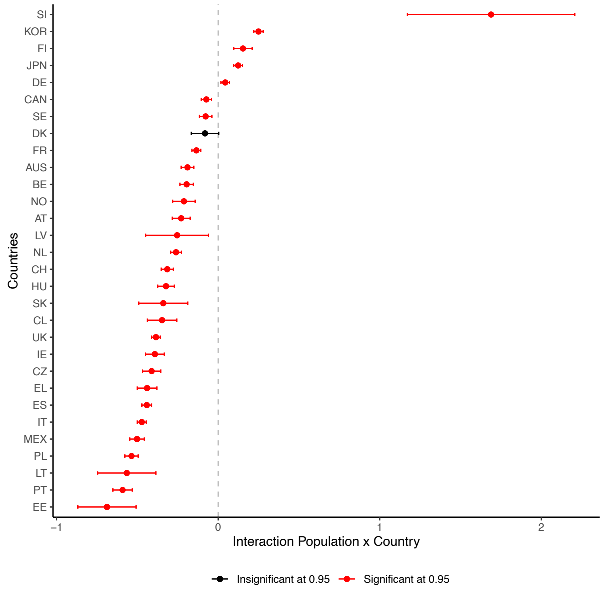

Figure 8: Variations in boosting across countries

Insights into sorting, i.e., innovation-intensive technologies concentrating in larger urban areas, were obtained by relating region-technology-specific patent numbers on the innovation-intensity of technologies (INNO_TECH) with a varying (region-specific) slope and varying intercept regression, to obtain a measure of each region's specialization in innovation-intensive technologies (see a summary of the regression in Table **12** in the Appendix). Subsequently, the region-specific slopes were regressed on region's population using a meta-regression. The outcome of the latter confirms the significantly positive relationship with a coefficient of 0.285^{***} (see Table 2). Accordingly, regions with larger populations are more strongly specialized in innovation-intensive technologies. That is, sorting significantly contributes to urban scaling.

	Dep: Coef. INNO_TECH
intercept	-2.626 (0.109) ***
log (Population)	0.285 (0.008) ***
FE (Dummies)	Countries
I^2	92.514
Test of moderators	107.043
Test of moderators p-value	0.000
Log Likelihood	-130.598
BIC	505.466
nobs	1108

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 2: Population and sorting

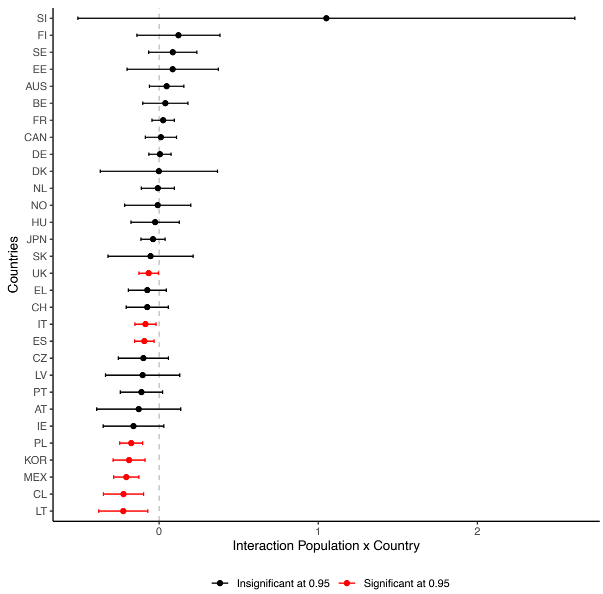

Figure 9: Variations in sorting across countries

Like boosting, sorting varies across countries. It was quantified by interacting regions' populations with country dummies in an extension of the previous meta-regression (the summary of the regression results is given in *Table **13*** in the Appendix). Figure 9 visualizes the coefficients obtained. For 22 countries, sorting is found not to be significantly different than that observed for the USA. Again, two countries (IS, LU) do not have enough observations to be tested against the reference (USA). In eight countries sorting is significantly weaker, which means their urban areas do not attract innovation-intensive technologies to the same extent as cities in the USA. Seven of these eight countries are also characterized by lower boosting than the USA (e.g., Poland (PL), Italy (IT), Lithuania (LT), Chile (CL), Mexico (MEX), United Kingdom (UK), and Spain (ES)). Yet, this does not imply that total scaling is necessarily lower than what is observed in the USA. For instance, Mexico has weaker boosting and sorting than the USA, but overall, urban scaling is stronger (Figure 5). This is due to two reasons. First, in the boosting and sorting estimations, all technologies are treated equally, while in the estimations of total scaling, they are (implicitly) weighted by their country-specific patent numbers. That is, the technology-specific estimations of boosting and sorting, do not consider countries being specialized in some technologies. Put differently, in the estimations of total scaling, countries' results differ because their patent portfolio are shaped by other technologies. Secondly, a globally patent-intensive technology (value of INNO_TECH) may, for country-specific reasons, not be patent-intensive in a country, e.g., its actual ratio of regional patents to population may be lower than the global average. Both effects are independent of the scaling argument and are hence not explored further. Consequently, in the empirical methodology, the empirically identified magnitudes of sorting and boosting do not add up to that of total scaling. Nevertheless, when explaining countries' total scaling coefficients with the country-specific boosting and sorting effects (see *Table **14*** in the Appendix), both effects jointly and significantly explain about three-quarters of total scaling (Table 3). According to these regressions, on its own, sorting has the much larger explanatory power of total scaling.
An interesting case is South Korea. It is the only country with lower sorting than the USA but stronger boosting. Accordingly, cities boost innovation activities, but the most innovative technologies are not more attracted to larger cities. It is beyond the scope of the paper to explain the special role of South Korea. However, it is clear is that despite the supposed universality of urban scaling, substantial heterogeneity exists between countries including very distinct scaling patterns that call for deeper analyses in future studies.

	Dep: Total scaling	**Dep: Total scaling**	**Dep: Total scaling**
(Intercept)	0.537 [0.053; 1.020]*	0.586 [0.274; 0.899]*	0.524 [0.217; 0.831]*
Average_boosting	1.180 [0.434; 1.926]*		0.343 [0.069; 0.617]*
Sorting		2.427 [1.487; 3.367]*	1.871 [1.013; 2.729]*
R^2	0.639	0.746	0.761
Adj. R^2	0.626	0.737	0.744
Num. obs.	31	31	31
RMSE	0.377	0.316	0.312

* Null hypothesis value outside the confidence interval.

Table 3: Contribution of boosting and sorting to total scaling

In summary, **research questions 2 and 3** are answerable: While boosting contributes to urban scaling, there are few technologies that experience an (urban) boosting effect on a global scale. The effect is primarily visible when zooming into specific countries (e.g., USA, Japan, and Germany), which means that the same technology shows distinct scaling properties in different countries. In addition, countries differ significantly in the magnitude of boosting. Both observations starkly contrast with the idea that urban scaling might be universal. A similar logic applies to sorting. More urbanized areas generally attract more innovation-intensive technologies, which contributes to their total innovation output and total urban scaling. This research shows that this holds across all countries as well. However, countries differ substantially in the strength of this effect. Accordingly, as total urban scaling is varying across the world, so does the relative relevance of the mechanisms at its roots (boosting and sorting).

4.3. Boosting and sorting and technological complexity

Research question 4 considers whether more complex technologies benefit more from boosting and whether sorting into innovation-intensive technologies is facilitated by more complex technologies being attracted to larger urban areas. Testing this is straightforward for boosting. For instance, Figure 10 gives a first intuitive visualization of the relationship between boosting and complexity. The 568 technology-specific boosting coefficients (one being the reference category) of Figure 3 (y-axis) were ordered by their corresponding complexity values (x-axis). The figure also features each technology's share in all patents (size of points). The increasing trend line suggests a positive relationship between complexity and boosting. This is confirmed with two meta-regressions. The first relates technologies' boosting coefficients (slope coefficients of the interaction of population and technology-dummies (Table **9** in the Appendix)) to their corresponding complexity values (first column in Table 4). The second explains the technology- and country-specific boosting coefficients (slope coefficients of the interaction of population, technology, and country dummies (Table **11** in the Appendix)) with complexity (second column in Table 4). In both cases, complexity obtains a significantly positive coefficient (see Table 4), implying that the boosting effect of population is more pronounced for more complex technologies. This means that innovation activities in complex technologies benefit more from being located in more populous areas than innovation activities in simpler technologies, which confirms what Balland et al. (2020) observed within the USA.

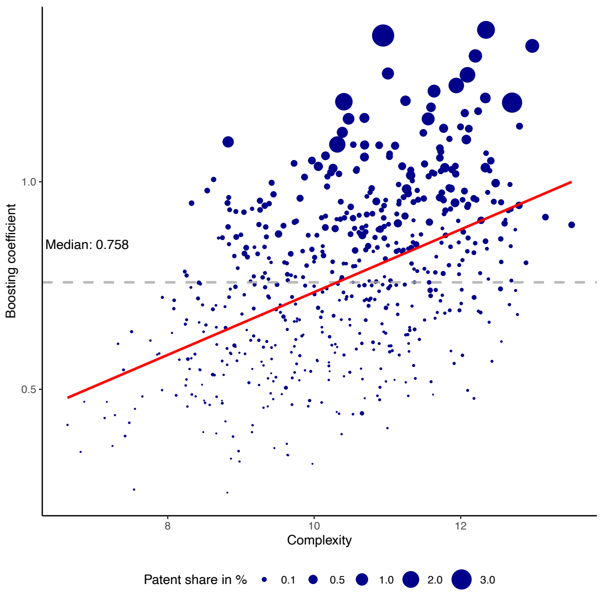

Figure 10: Visualization of the relationship between boosting and complexity

	Dep: Boosting coefficients	Dep: Country-specific boosting coefficients
Intercept	-1.015*** (0.060)	-0.969 (0.024) ***
Complexity	0.074*** (0.006)	0.085 (0.002) ***
FE (Dummies)	No	Countries
I^2	50.475	30.732
Test of moderators	170.323	274.886
Test of moderators p-value	0.000	0.000
Log Likelihood	166.261	-5856.485
BIC	-313.559	12023.234
nobs	558	12144

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$

Table 4: The relationship between boosting and complexity

Testing the relationship between complexity and sorting is more difficult. Unfortunately, it is not possible to simply calculate the concentration of technologies in regions and explain this with complexity, as this gives insights into the spatial distribution of complex technologies but not if populous regions attract more innovation-intensive technologies because they are also more complex. Therefore, a different approach was used. Complexity was integrated into the previous approach of testing sorting by interacting the varying slope components (INNO_TECH*REG) with complexity (COMPLEX*INNO_TECH*REG). This resulted in three sets of varying slope values. The first set, which was already included in the initial regression, approximates the degree of sorting within regions into innovation-intensive technologies (INNO_TECH). The second provides insights into the sorting of regions into complex technologies (COMPLEX). The third reflects the tendency of regions to attract innovation-intensive technologies that are also complex (COMPLEX*INNO_TECH). Each set of coefficients (region-specific slope parameters) was subsequently related to population using a meta-regression approach. If complexity plays a significant role in sorting, the relation between INNO_TECH's coefficients and population is expected to weaken in comparison to what is observed without complexity (Table 2). Secondly, a significantly positive relationship between population and the coefficients for COMPLEX*INNO_TECH suggests that sorting is more pronounced for complex innovation-intensive technologies.

Working with interaction effects is tricky because the interpretation of the main effects is conditional on the significance of the interaction effects. As this was the case here, the meta-regressions for COMPLEX*INNO_TECH was estimated using the full sample of observations and those for INNO_TECH and COMPLEX excluding regions with significant coefficients of COMPLEX*INNO_TECH (879 of 1108 regions).[13] The regression outcomes are presented in Table 5. For completeness, the results for INNO_TECH and COMPLEX using the full sample of observations are reported in *Table **15*** in the Appendix. Moreover, to assess changes in INNO_TECH's coefficients due to the consideration of COMPLEX, the exercise was repeated and the relationship between population and the coefficients of INNO_TECH and COMPLEX was estimated when the latter two had been estimated without their interaction (see *Table **16*** in the Appendix).

Across all specifications, population has a significantly positive relationship with INNO_TECH and COMPLEX (columns 1 and 2 in Table 5). Accordingly, more innovation-intensive and

	INNO_TECH	**COMPLEX**	**INNO_TECH*COMPLEX**
intercept	-2.522 (0.487) ***	-0.494 (0.090) ***	-0.031 (0.083)
log (Population)	0.221 (0.025) ***	0.039 (0.005) ***	0.009 (0.004) *
FE (Countries)	Yes	Yes	Yes
I^2	51.880	83.039	79.719
Test of moderators	8.966	5.409	2.443
Test of moderators p-value	0.000	0.000	0.006
Log Likelihood	-1056.116	468.646	488.791
BIC	2341.409	-708.316	-733.904
nobs	879	879	1090

Table 5: Meta-regression for sorting and complexity

complex technologies are attracted to more populous places.

However, the relation between population and INNO_TECH weakens only slightly when considering complexity: From an initial value of 0.285^{***} (Table 2), the coefficient drops to 0.260^{***} when varying (region-specific) slopes for complexity are added (first column in *Table **16***) and to 0.221^{***} in the case that complexity and the interaction of INNO_TECH and COMPLEX are considered (first column in Table 5). This means that complexity shares little

[13] A threshold of $p<0.05$ is used. Moreover, we also estimated the regression excluding the interaction of COMPLEX and INNO_TECH. The results remain the same.

variance with INNO_TECH, which correlates with population numbers. This is also indicated by the barely significant coefficient of population when it is regressed on the slope parameters of the interaction of INNO_TECH*COMPLEX (third column in Table 5). That is, the analysis finds limited evidence that sorting into complex technologies is a facilitator of urban scaling of innovation when controlling for the innovation intensity of technologies. To a certain degree, this resembles the relatively low bivariate correlation of 0.31^{***} of the complexity of technologies and their innovation-intensity.

In sum, **research question 4** can be answered: The boosting effect is clearly larger for more complex technologies implying that they benefited more from more urban environments. More populous areas also tended to specialize in more innovation-intensive technologies. While larger regions also attract more complex technologies, this is not the major source of the sorting effect that contributes to the urban scaling of innovation.

5. Discussion and Conclusion

The paper contributes to the recent literature on urban scaling of innovation, which is concerned with the degree to which innovation concentrates disproportionately in more populous regions (Bettencourt et al., 2010; Bettencourt et al., 2007; Fritsch and Wyrwich, 2021; Lobo et al., 2013; Mewes, 2019). Using a novel data set including 1,120 functional urban areas in 33 countries around the globe, this research adds comprehensive cross-country evidence of the existence of urban scaling while simultaneously demonstrating that it differs across countries. The research distinguishes between boosting and sorting as basic mechanisms underlying total urban scaling. It is shown that the effect of boosting, which refers to the same technological activity generating more innovation output per inhabitant in larger cities, varies substantially between countries. A similar logic applies to sorting, which captures the tendency of larger cities to specialize in technologies with higher innovation intensities than smaller ones. While this analysis suggests that sorting explains a larger share of total urban scaling of innovation, there are noticeable differences between countries. For instance, in eight countries, boosting and sorting were both less pronounced than in the USA. By contrast, in South Korea, boosting was stronger and sorting weaker than what was observed in the USA. Consequently, our study shows that while urban scaling is a global phenomenon, there is substantial international heterogeneity in its magnitude and, even more crucially, in its underlying mechanisms.

This research also confirms that complexity is related to urban scaling, as suggested by Balland et al. (2020). More complex technologies, indeed, also benefit more (than less complex technologies) from being located in larger urban areas. However, only weak evidence is found to suggest that for populous locations, specialization in complex technologies contributes to the overall sorting effect. Given that sorting has greater importance for urban scaling of innovation relative to boosting, the attraction of complex technologies to cities is not a primary contributor to this process.

These findings have at least two crucial policy implications. First, Fritsch and Wyrwich (2021) indicate that innovation is not bound to (large) cities. Smaller and more remote places are also centers of technological advancements suggesting that (public) investments into the technological capabilities of these places (e.g., research centers) can be fruitful. However, this greatly varies between countries. Some countries (e.g., the Netherlands and Switzerland) were among the most innovative countries in the world and yet, in their case, hardly any (technological) innovation processes were subject to urban scaling. Apparently, being a leader in innovation does not require urban scaling: a national innovation system less spatially concentrated than in the USA can be at least as successful. However, this does not apply to complex technologies, which supports the second policy implication. Innovation in these technologies benefits from urban environments, and while inventors from smaller cities also contribute to and utilize them, (large) cities offer substantial locational advantages boosting research activities therein. Consequently, (public) investments contributing to their development are better placed in cities. Unfortunately, this may further stimulate spatial inequality, because competencies in complex technologies in particular, are linked to economic growth (Mewes and Broekel, 2022). Consequently, smart policies are required to remedy this conflict between the core aims of innovation policies (supporting complex technologies) and regional policies (reducing regional inequality).

These implications must be taken with a grain of salt, as the study's empirical approach has several limitations. Most importantly, the research only considers patents as indicators of innovation, which implies several kinds of biases. Spatial dependencies were addressed only by including country dummies and clustered standard errors, although more advanced approaches are available. Furthermore, most of the regressions were rather bivariate and only controlled for influences at the country level. The regressions exclusively considered log-log relationships and disentangling potential endogenous relationships was not even attempted. The investigations rely on a cross-sectional approach, which would be fascinating to extend to a longitudinal format in the style of Mewes (2019). However, from an empirical perspective, reliable data on a global scale is nearly impossible to gather. From a theoretical perspective, arguments were not presented as to how and why the dynamics of scaling, boosting, and sorting relate to one another or develop over time. Recently, Bettencourt et al. (2020) and Mewes (2019) began to explore this topic.

Except for the reliance on patent data, which is simply due to the lack of alternatives, many of the study's limitations are by choice. That is, the study was modeled after other studies in the urban scaling of innovation literature are conducted to generate comparable results for "typical" outcomes (Balland et al., 2020; Fritsch and Wyrwich, 2021), while still being able to contribute to the advancement of this literature stream.

Future research on urban scaling of innovation should address two questions (one empirical and one provocative) and consider at least one empirical recommendation. The two questions are:

- Why does super-linear scaling only hold for total patent numbers but not for many individual technologies?
- Recent developments in the scaling framework (e.g., Youn et al. 2016) emphasize that urban scaling is an outcome of the agglomeration of more diverse knowledge in larger places. This study confirms this in the context of innovation. However, which activities precisely are located in larger regions, for which reasons, and why do improvements in communication and transportation not (yet) erode this feature of larger places?

Answering these questions will allow for a better understanding of the emergence of urban scaling of innovation in the technological and geographical dimensions. The empirical recommendation of this research is to differentiate urban scaling into sorting and boosting effects. In itself, this is not novel given that it has been part of the conceptual framework of the measurement of innovation performance of spatial units for a long time (see, e.g., Brenner and Broekel, 2011). However, for too long, the urban scaling literature has paid little attention to it. For instance, Bettencourt (2013) focuses on how city size may shape the interactions of its inhabitants (or subsystems) in his discussion on the origins of urban scaling. But the degree to which city size may act as a selection mechanism attracting (and breeding) specific types of competencies and resources, which in turn may contribute to urban scaling, has only recently been discussed in this context (Balland et al., 2020; Gomez-Lievano et al., 2017; Youn et al., 2016). In particular, the idea of cities providing the necessary conditions for more (economically) complex activities to emerge and grow, is a promising new direction to follow in answering the question above (Balland et al., 2022). Even though this study casts some doubts on the role of complexity in this context, this shouldn't discourage endeavors in this direction. This study has focused on technological complexity and not on economic complexity.

Notwithstanding a certain degree of relatedness, the two types of complexity represent distinct dimensions with specific features. They are, hence, likely party to different dynamics; yet another area calling for more research.
Lastly, stronger interactions between the economic geography and urban scaling communities would be advantageous for future research. The urban scaling literature will clearly benefit from the insights into place-specificity and potential explanations for deviations from average urban scaling relations (e.g., differences between countries) that have been discussed and explored for a long time in economic geography. Conversely, regional science and economic geography scholars will benefit from the scaling literature's rigorous translation of micro-level dynamics into system-level features and dynamics.

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Appendix

	Name	Country Code	Country Patent Code	Numbers of FUA
1	Australia	AUS	AU	18
2	Austria	AUT	AT	6
3	Belgium	BEL	BE	14
4	Canada	CAN	CA	26
5	Chile	CHL	CL	26
6	Czech Republic	CZE	CZ	15
7	Switzerland	CHE	CH	12
8	Colombia	COL		53
9	Denmark	Denmark	DK	4
10	Estland	EST	EE	3
11	Greece	GRC/EL	EL	13
12	Finland	FIN	FI	7
13	France	FRA	FR	88
14	Germany	DEU	DE	96
15	Hungary	HUN	HU	19
16	Island	ISL	IS	1
17	Ireland	IRL	IE	5
18	Italy	ITA	IT	84
19	Japan	JPN	JP	61
20	South Korea	KOR	KR	22
21	Latvia	LVA	LV	4
22	Lithuania	LTU	LT	6
23	Luxembourg	LUX	LU	1
24	Mexico	MEX	MX	92
25	Netherlands	NLD	NL	35
26	Norway	NOR	NO	6
27	Poland	POL	PL	58
28	Portugal	PRT	PT	13
29	Slovakia	SVK	SK	8
30	Slovenia	SVN	SI	2
31	Spain	ESP	ES	81
32	Sweden	SWE	SE	12
33	USA	USA	US	211
34	UK	GBR	GB	96

Table 6: Overview of considered countries

Country	vars	n	mean	sd	median	min	max	skew	kurtosis
AT	**Patents**	**6**	**3095.67**	**2539.83**	**2277**	**995**	**7462**	**0.66**	**-1.35**
AT	**Patents Fractional**	**6**	**2432.96**	**1986.74**	**1808.84**	**729.29**	**5813.06**	**0.63**	**-1.4**
AT	**Population**	**6**	**794933.86**	**923289.57**	**471744.82**	**248574.29**	**2655059.79**	**1.28**	**-0.21**
AUS	**Patents**	**18**	**1108.78**	**2204.74**	**213.5**	**25**	**8760**	**2.47**	**5.41**
AUS	**Patents Fractional**	**18**	**891.01**	**1847.56**	**151.14**	**21**	**7428.69**	**2.57**	**5.97**
AUS	**Population**	**18**	**905367.91**	**1311310.25**	**254340.46**	**107000**	**4409081.29**	**1.68**	**1.48**
BE	**Patents**	**14**	**1610.71**	**2494.44**	**523.5**	**54**	**9349**	**2.11**	**3.72**
BE	**Patents Fractional**	**14**	**993.44**	**1553.95**	**324.87**	**39.42**	**5759.75**	**2.08**	**3.48**
BE	**Population**	**14**	**462397.29**	**628001.16**	**183615.11**	**70000**	**2409237.86**	**2.1**	**3.7**
CAN	**Patents**	**26**	**3307.85**	**5565.12**	**848**	**101**	**23953**	**2.25**	**4.88**
CAN	**Patents Fractional**	**26**	**2596.26**	**4443.72**	**631.78**	**64.27**	**19024.13**	**2.25**	**4.82**
CAN	**Population**	**26**	**884448.15**	**1398449.47**	**363501.79**	**85000**	**6313701.57**	**2.68**	**6.85**
CH	**Patents**	**12**	**2812.08**	**3583.63**	**1481.5**	**148**	**13033**	**1.88**	**2.61**
CH	**Patents Fractional**	**12**	**2132.4**	**2789.65**	**1126.06**	**104.45**	**10328.1**	**2.04**	**3.27**
CH	**Population**	**12**	**293050.51**	**335498.62**	**133269.43**	**23000**	**1197450.21**	**1.52**	**1.54**
CL	**Patents**	**22**	**47.45**	**168.57**	**6**	**1**	**798**	**4**	**14.87**
CL	**Patents Fractional**	**22**	**39.67**	**140.95**	**3.92**	**0.25**	**666.47**	**3.98**	**14.78**
CL	**Population**	**22**	**578997.12**	**1395899.68**	**216500**	**54000**	**6737076.46**	**3.88**	**14.22**
CZ	**Patents**	**15**	**283.07**	**447.09**	**162**	**4**	**1707**	**2.25**	**4.12**
CZ	**Patents Fractional**	**15**	**208.2**	**344.38**	**111.83**	**2.67**	**1319.16**	**2.32**	**4.43**
CZ	**Population**	**15**	**360280.57**	**502677.35**	**168478.15**	**74500.62**	**2014561.07**	**2.36**	**4.89**
DE	**Patents**	**96**	**7534.03**	**13202.03**	**3335.5**	**183**	**91844**	**4.27**	**21.54**
DE	**Patents Fractional**	**96**	**5349.39**	**10142.92**	**2190.44**	**122.08**	**71969.76**	**4.59**	**24.25**
DE	**Population**	**96**	**628611.88**	**866406.27**	**338191.71**	**62098.93**	**5211672.79**	**3.47**	**13.35**
DK	**Patents**	**4**	**1875.25**	**2104.78**	**1009.5**	**473**	**5009**	**0.72**	**-1.71**
DK	**Patents Fractional**	**4**	**1592.74**	**1795.3**	**841.96**	**419.12**	**4267.92**	**0.72**	**-1.71**
DK	**Population**	**4**	**722197.61**	**691426.66**	**418029.54**	**298917.29**	**1753814.07**	**0.73**	**-1.7**
EE	**Patents**	**3**	**226.33**	**239.2**	**189**	**8**	**482**	**0.15**	**-2.33**
EE	**Patents Fractional**	**3**	**182.18**	**195.59**	**149.74**	**4.83**	**391.97**	**0.16**	**-2.33**
EE	**Population**	**3**	**219782.09**	**281106.72**	**85699**	**30821.12**	**542826.14**	**0.37**	**-2.33**
EL	**Patents**	**13**	**164.77**	**403.21**	**15**	**5**	**1479**	**2.63**	**5.7**
EL	**Patents Fractional**	**13**	**137.63**	**348.56**	**11.67**	**3.17**	**1277.58**	**2.66**	**5.81**
EL	**Population**	**13**	**455451.39**	**1023594.75**	**110000**	**27447.2**	**3742265.29**	**2.53**	**5.2**
ES	**Patents**	**80**	**331.84**	**1112.92**	**66**	**1**	**7751**	**5.61**	**31.83**
ES	**Patents Fractional**	**80**	**286.43**	**971.29**	**54.88**	**1**	**6707.11**	**5.59**	**31.52**
ES	**Population**	**80**	**362770.9**	**885935.75**	**108909.59**	**21269.8**	**6264812.86**	**5.24**	**29.06**
FI	**Patents**	**7**	**5143.71**	**6328.61**	**2988**	**718**	**18577**	**1.25**	**-0.02**
FI	**Patents Fractional**	**7**	**4428.34**	**5508.48**	**2465.93**	**629.83**	**16166.72**	**1.27**	**0.02**
FI	**Population**	**7**	**397314.03**	**421322.99**	**236914.29**	**128227.21**	**1325265.36**	**1.44**	**0.41**
FR	**Patents**	**83**	**2698.16**	**10114.58**	**885**	**70**	**90887**	**8.02**	**66.67**
FR	**Patents Fractional**	**83**	**2210.12**	**8865.29**	**628.18**	**48.5**	**79849.18**	**8.12**	**67.9**
FR	**Population**	**83**	**474722.47**	**1354713.41**	**185764.64**	**51409.21**	**12282292.2**	**7.99**	**66.56**
HU	**Patents**	**19**	**237.84**	**662.23**	**79**	**16**	**2958**	**3.63**	**11.99**
HU	**Patents Fractional**	**19**	**184.14**	**535.03**	**54.45**	**11.58**	**2383.31**	**3.64**	**12.03**

HU	**Population**	**19**	**302225.89**	**627154.09**	**128452.46**	**76929.15**	**2873415.93**	**3.61**	**11.88**
IE	**Patents**	**5**	**1387.2**	**1651.99**	**814**	**165**	**4287**	**0.97**	**-1.03**
IE	**Patents Fractional**	**5**	**1053.33**	**1272.66**	**644.31**	**102.09**	**3286.68**	**0.97**	**-1.03**
IE	**Population**	**5**	**459869.07**	**677884.76**	**140769.07**	**57470.07**	**1652469.93**	**0.99**	**-1.03**
IS	**Patents**	**1**	**435**		**435**	**435**	**435**		
IS	**Patents Fractional**	**1**	**356.37**		**356.37**	**356.37**	**356.37**		
IS	**Population**	**1**	**218591.07**		**218591.07**	**218591.07**	**218591.07**		
IT	**Patents**	**84**	**786.69**	**1897.82**	**303**	**6**	**15643**	**6.09**	**42.66**
IT	**Patents Fractional**	**84**	**646.46**	**1596.22**	**237.08**	**4.33**	**12990.97**	**5.96**	**40.82**
IT	**Population**	**84**	**350479.61**	**753831.04**	**131688.25**	**25594.29**	**4630304.29**	**4.31**	**18.87**
JPN	**Patents**	**61**	**58050.51**	**259107.75**	**7155**	**287**	**1898954**	**6.14**	**39.39**
JPN	**Patents Fractional**	**61**	**54607.95**	**248535.38**	**6150.56**	**240.92**	**1825144.72**	**6.18**	**39.8**
JPN	**Population**	**61**	**1636921.62**	**4903505.47**	**591720.57**	**163000**	**34562643.9**	**5.53**	**32.08**
KOR	**Patents**	**22**	**75968.09**	**212251.55**	**24560.5**	**1126**	**1009557**	**3.85**	**14.02**
KOR	**Patents Fractional**	**22**	**58342.66**	**182133.5**	**15433.23**	**641.9**	**865945.77**	**3.95**	**14.58**
KOR	**Population**	**22**	**1918763.25**	**4965501.4**	**560000.88**	**134000**	**23701129.3**	**3.82**	**13.84**
LT	**Patents**	**6**	**70.83**	**104.74**	**12**	**1**	**256**	**0.82**	**-1.25**
LT	**Patents Fractional**	**6**	**53.17**	**79.83**	**10.25**	**1**	**199.42**	**0.91**	**-1.03**
LT	**Population**	**6**	**220206.37**	**283795.66**	**69344.35**	**11322**	**704781.21**	**0.73**	**-1.43**
LU	**Patents**	**1**	**1898**		**1898**	**1898**	**1898**		
LU	**Patents Fractional**	**1**	**1499.41**		**1499.41**	**1499.41**	**1499.41**		
LU	**Population**	**1**	**489341.36**		**489341.36**	**489341.36**	**489341.36**		
LV	**Patents**	**4**	**153.25**	**283.85**	**13**	**8**	**579**	**0.75**	**-1.69**
LV	**Patents Fractional**	**4**	**135.49**	**254.88**	**9.92**	**4.33**	**517.79**	**0.75**	**-1.69**
LV	**Population**	**4**	**304964.2**	**458039.24**	**87328.1**	**53615.25**	**991585.36**	**0.75**	**-1.69**
MEX	**Patents**	**77**	**59.17**	**201.7**	**8**	**1**	**1508**	**5.59**	**34.04**
MEX	**Patents Fractional**	**77**	**47.04**	**169.62**	**5**	**0.17**	**1318.02**	**6.02**	**39.53**
MEX	**Population**	**77**	**890847.44**	**2177588.85**	**454184.67**	**153000**	**18663829.6**	**7.15**	**54.79**
NL	**Patents**	**35**	**1456.09**	**2214.25**	**882**	**101**	**11539**	**3.05**	**10.09**
NL	**Patents Fractional**	**35**	**1004.69**	**1693.57**	**498.99**	**65.02**	**9037.14**	**3.35**	**12.12**
NL	**Population**	**35**	**377247.49**	**514015.02**	**203561.64**	**49858.29**	**2627361.36**	**3**	**9.22**
NO	**Patents**	**6**	**1427.5**	**1563.7**	**1088**	**56**	**4360**	**0.91**	**-0.79**
NO	**Patents Fractional**	**6**	**1239.61**	**1355.16**	**944.84**	**40.67**	**3781.31**	**0.91**	**-0.79**
NO	**Population**	**6**	**367152.92**	**407772.42**	**265428.61**	**43723.36**	**1163414.71**	**1.11**	**-0.48**
PL	**Patents**	**58**	**171.79**	**371.68**	**32**	**2**	**2054**	**3.25**	**11.19**
PL	**Patents Fractional**	**58**	**141.53**	**311.48**	**18.92**	**1**	**1695.06**	**3.19**	**10.67**
PL	**Population**	**58**	**336918.17**	**550274.19**	**134887.05**	**28683.2**	**2976845.79**	**3.3**	**11.62**
PT	**Patents**	**13**	**158.46**	**244.52**	**43**	**3**	**842**	**1.7**	**1.9**
PT	**Patents Fractional**	**13**	**130.23**	**204.5**	**28.78**	**1.5**	**697.04**	**1.67**	**1.76**
PT	**Population**	**13**	**433649.25**	**807164.02**	**120000**	**60055.08**	**2883921.07**	**2.2**	**3.66**
SE	**Patents**	**12**	**3444**	**4784.05**	**1535.5**	**294**	**16121**	**1.56**	**1.29**
SE	**Patents Fractional**	**12**	**2881.94**	**4093.69**	**1210.22**	**227.58**	**13713.08**	**1.56**	**1.27**
SE	**Population**	**12**	**398653.75**	**549175.7**	**167121.79**	**59576.07**	**1949451.71**	**1.87**	**2.41**
SI	**Patents**	**2**	**673.5**	**693.67**	**673.5**	**183**	**1164**	**0**	**-2.75**
SI	**Patents Fractional**	**2**	**616.5**	**662.68**	**616.5**	**147.92**	**1085.08**	**0**	**-2.75**

SI	**Population**	**2**	**410317.21**	**125871.27**	**410317.21**	**321312.79**	**499321.64**	**0**	**-2.75**
SK	**Patents**	**8**	**74.38**	**121.58**	**33**	**10**	**372**	**1.78**	**1.51**
SK	**Patents Fractional**	**8**	**58.19**	**100.38**	**24.02**	**7**	**304.57**	**1.8**	**1.56**
SK	**Population**	**8**	**185117.31**	**182043.38**	**119817.98**	**65956.67**	**607124**	**1.47**	**0.67**
UK	**Patents**	**96**	**1217.58**	**3045.69**	**527**	**48**	**27983**	**7.27**	**59.59**
UK	**Patents Fractional**	**96**	**921.12**	**2356.06**	**369.33**	**18.71**	**21686.65**	**7.31**	**60.24**
UK	**Population**	**96**	**504575.4**	**1214937.07**	**194695.61**	**39330.57**	**11063787.8**	**7.07**	**56.91**
USA	**Patents**	**211**	**9840.51**	**26881.63**	**2171**	**9**	**291771**	**6.77**	**59.46**
USA	**Patents Fractional**	**211**	**7087.44**	**20781.95**	**1513.07**	**5.83**	**236460.16**	**7.45**	**71.34**
USA	**Population**	**211**	**1056362.91**	**2162243**	**419666.93**	**58000**	**19425328.7**	**5.52**	**37.4**

Table 7: Country-specific descriptives

Table **7** provides insights into the regions across the countries considered in this study. The USA has the largest number (211) with the UK (96) and Germany (96) having less than half that number. This distribution exemplifies the substantial differences in the spatial distribution of population between countries. For instance, Japan has about twice as many inhabitants than the UK. Yet, it is divided into fewer FUAs (61) than the UK (96).

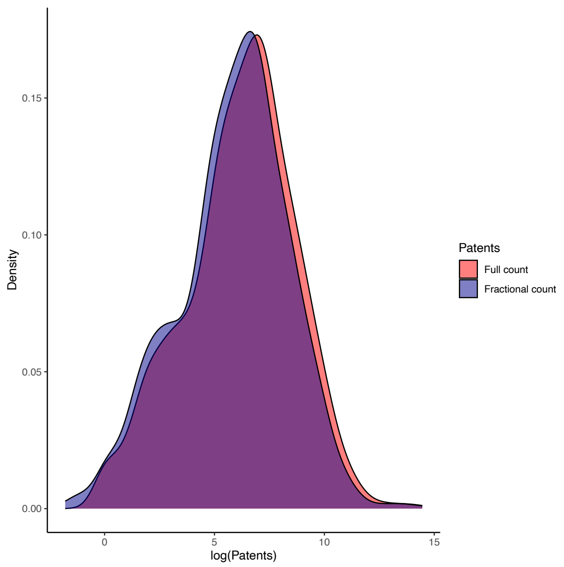

Figure 11: Distribution of patents across FUA

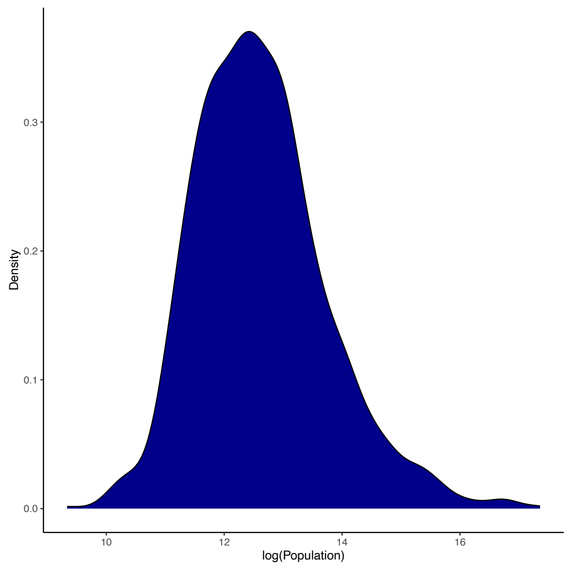

Figure 12: Distribution of population across FUA

Figure 11 shows the distribution of patents across urban areas. It also features the comparison between the fractional and full counting of patents, which confirms that there are hardly any distributional differences between the two.

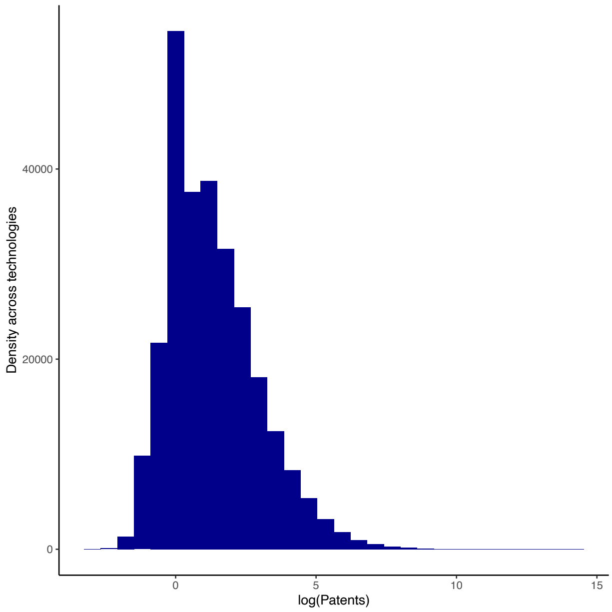

Figure 13: Distribution of patents across technologies

	Dep.: log(Patents)
(Intercept)	-10.519 [-12.070; -8.968]*
log(Population)	1.362 [1.247; 1.477]*
AT	-0.470 [-0.757; -0.182]*
AUS	0.084 [-0.083; 0.251]
BE	-0.177 [-0.459; 0.104]
CAN	-0.060 [-0.258; 0.137]
CH	-0.473 [-0.821; -0.125]*
CL	0.199 [-0.057; 0.456]
CZ	-0.057 [-0.538; 0.424]
DE	-0.110 [-0.328; 0.108]
DK	-0.205 [-0.549; 0.139]
EE	0.049 [-0.564; 0.662]
EL	-0.115 [-0.255; 0.025]
ES	-0.145 [-0.353; 0.063]
FI	0.001 [-0.278; 0.281]
FR	-0.151 [-0.333; 0.030]
HU	-0.075 [-0.329; 0.179]
IE	-0.526 [-0.842; -0.210]*
IT	-0.248 [-0.543; 0.046]
JPN	0.016 [-0.210; 0.241]
KOR	-0.146 [-0.373; 0.082]
LT	-0.145 [-0.313; 0.022]
LV	0.177 [-0.215; 0.568]
MEX	0.315 [0.058; 0.573]*
NL	-0.260 [-0.515; -0.005]*
NO	-0.050 [-0.431; 0.332]
PL	0.002 [-0.202; 0.206]
PT	-0.114 [-0.582; 0.355]
SE	-0.147 [-0.374; 0.080]
SI	3.158 [3.044; 3.273]*
SK	0.054 [-0.342; 0.450]
UK	-0.398 [-0.567; -0.229]*
Reference	USA
FE (Dummies)	Country
Robust std.err	Yes
Num. obs.	1120
R^2 (full model)	0.883
Adj. R^2 (full model)	0.876
*** 0 outside the 95% confidence interval.**	

Table 8: Country-specific scaling as varying slopes

	Dep.: log(Patents)
log(Population)	1.001 [0.815; 1.188]*
… 567 coefficients shown in Figure 5 …	
Reference	B32B
FE	Technology and Country
Robust std.err	Yes
Num. obs.	271623
Num. groups: Tech^Country	15176
R^2 (full model)	0.598
R^2 (proj model)	0.424
Adj. R^2 (full model)	0.573
Adj. R^2 (proj model)	0.423
*** 0 outside the confidence interval.**	

Table 9: Boosting regression with technology-specific boosting coefficients

	Coef. log(Population)
intercept	-0.087 (0.009)***
AT	-0.229 (0.028)***
AUS	-0.190 (0.020)***
BE	-0.195 (0.021)***
CAN	-0.073 (0.016)***
CH	-0.315 (0.019)***
CL	-0.347 (0.047)***
CZ	-0.412 (0.029)***
DE	0.044 (0.014)**
DK	-0.082 (0.043)
EE	-0.688 (0.092)***
EL	-0.440 (0.031)***
ES	-0.442 (0.015)***
FI	0.153 (0.029)***
FR	-0.135 (0.014)***
HU	-0.323 (0.026)***
IE	-0.392 (0.030)***
IT	-0.473 (0.014)***
JPN	0.124 (0.014)***
KOR	0.249 (0.015)***
LT	-0.566 (0.092)***
LV	-0.254 (0.099)*
MEX	-0.502 (0.023)***
NL	-0.261 (0.017)***
NO	-0.212 (0.035)***
PL	-0.536 (0.021)***
PT	-0.592 (0.031)***
SE	-0.078 (0.020)***
SI	1.689 (0.264)***
SK	-0.340 (0.077)***
UK	-0.385 (0.014)***
I^2	38.169
Test of moderators	18995.921
Test of moderators‘ p-value	0.000
BIC	13620.105
nobs	12390
*****p < 0.001; **p < 0.01; *p < 0.05**	

Table 10: Meta-regression of boosting effect across countries

	Dep.: log(Patents)
(Intercept)	-12.175 [-14.285; -10.065]*
log(Population)	1.000 [0.843; 1.157]*
… 27541 coefficients …	
Reference Tech	B32B
Reference Country	USA
FE (Dummies)	TECH and COUNTRY
Robust std.err	No
Num. obs.	271623
R^2 (full model)	0.630
Adj. R^2 (full model)	0.589

Table 11: Initial boosting regression across technologies and regions

	Dep. log(Patents)
(Intercept)	0.329 [0.290; 0.369]*
INNO_TECH	0.001 [-0.054; 0.055]
… 1109 coefficients ...	
FE (Dummies)	Regions
Clustered std.err	TECH and COUNTRY
Num. obs.	271623
R^2 (full model)	0.653
Adj. R^2 (full model)	0.650
* 0 outside the confidence interval.	

Table 12: Initial specialization regression (sorting)

	Coef. INNO_TECH
intercept	-3.361 (0.228)***
log(Population)	0.341 (0.017)***
AT	-0.128 (0.135)
AUS	0.047 (0.055)
BE	0.039 (0.072)
CAN	0.011 (0.050)
CH	-0.075 (0.067)
CL	-0.224 (0.064)***
CZ	-0.099 (0.080)
DE	0.005 (0.036)
DK	-0.002 (0.188)
EE	0.085 (0.146)
EL	-0.074 (0.061)
ES	-0.093 (0.031)**
FI	0.121 (0.133)
FR	0.025 (0.036)
HU	-0.025 (0.077)
IE	-0.161 (0.097)
IT	-0.086 (0.034)*
JPN	-0.038 (0.039)
KOR	-0.189 (0.051)***
LT	-0.225 (0.078)**
LV	-0.104 (0.119)
MEX	-0.206 (0.040)***
NL	-0.008 (0.053)
NO	-0.009 (0.106)
PL	-0.175 (0.037)***
PT	-0.111 (0.068)
SE	0.086 (0.077)
SI	1.051 (0.796)
SK	-0.054 (0.136)
UK	-0.066 (0.031)*
Reference country	USA
FE (Dummies)	Countries
I2	91.943
Test of moderators	61.311
Test of moderators‘ p-value	0.000
BIC	639.481
nobs	1108
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$	

Table 13: Meta-regression of sorting and country differences

Name	Country Patent Code	Total scaling	Boosting	Sorting
Austria	AT	0,892	0,6725	0,213
Australia	AU	1,446	0,7115	0,388
Belgium	BE	1,185	0,7065	0,38
Canada	CA	1,302	0,8285	0,352
Switzerland	CH	0,889	0,5865	0,266
Chile	CL	1,561	0,5545	0,117
Czech Republic	CZ	1,305	0,4895	0,242
Germany	DE	1,252	0,9455	0,346
Denmark	DK	1,157	0,8195	0,339
Estland	EE	1,411	0,2135	0,426
Greece	EL	1,247	0,4615	0,267
Spain	ES	1,217	0,4595	0,248
Finland	FI	1,363	1,0545	0,462
France	FR	1,211	0,7665	0,366
UK	GB	0,964	0,5165	0,275
Hungary	HU	1,287	0,5785	0,316
Ireland	IE	0,836	0,5095	0,18
Island	IS			
Italy	IT	1,114	0,4285	0,255
Japan	JP	1,378	1,0255	0,303
South Korea	KR	1,216	1,1505	0,152
Lithuania	LT	1,217	0,3355	0,116
Luxembourg	LU			
Latvia	LV	1,539	0,6475	0,237
Mexico	MX	1,677	0,3995	0,135
Netherlands	NL	1,102	0,6405	0,333
Norway	NO	1,312	0,6895	0,332
Poland	PL	1,364	0,3655	0,166
Portugal	PT	1,218	0,3095	0,23
Sweden	SE	1,215	0,8235	0,427
Slovenia	SI	4,52	2,5905	1,392
Slovakia	SK	1,416	0,5615	0,287
USA	US	1,362	0,803	0,341

Table 14: Overview: scaling, boosting, and sorting effects

	INNO_TECH	COMPLEX
intercept	-3.126 (0.143)***	-0.542 (0.050)***
log(Population)	0.310 (0.011)***	0.035 (0.004)***
I2	94.252	90.810
Test of moderators	755.141	79.011
Test of moderators‘ p-value	0.000	0.000
Log Likelihood	-617.153	540.242
BIC	1255.328	-1059.473
nobs	1107	1103
*****p < 0.001; **p < 0.01; *p < 0.05**		

Table 15: Meta-regression of sorting and complexity - full sample

	INNO_TECH	COMPLEX
intercept	-2.285 (0.178)***	-0.448 (0.081)***
log(Population)	0.260 (0.009)***	0.033 (0.004)***
I^2	89.164	90.254
Test of moderators	75.671	4.582
Test of moderators‘ p-value	0.000	0.000
Log Likelihood	-253.800	543.207
BIC	751.838	-842.308
nobs	1107	1103
*****p < 0.001; **p < 0.01; *p < 0.05**		

Table 16: Meta-regression sorting and complexity – no interaction of INNO_TECH & COMPLEX