DRAFT: PLEASE DO NOT CITE WITHOUT PERMISSION

Prolific Rural Inventors Raise Questions about the Geography of Invention

Authors: Timothy R. Wojan[1]*, Kathryn R. Dotzel[2], Andrew A. Toole[1,3], Sarah A. Low[1]

Affiliations:

[1] Economic Research Service, US Department of Agriculture.

[2] The Ohio State University

[3] Centre for European Economic Research (ZEW), Mannheim, Germany

*Correspondence to: twojan@ers.usda.gov

Abstract: Patents per capita is a widely used innovation indicator. Rural areas generally perform very poorly using this metric, suggesting that inventive activity that leads to patents is an urban phenomenon. However, newly available inventor-disambiguated patenting data demonstrate that inventions per inventor are roughly equal across urban and rural areas. A critical assessment of the patents per capita measure questions its construct validity. An alternative measure that identifies an exemplary "inventive class" and does not confound the patenting rate with irrelevant information is constructed. This allows the decomposition of overall patenting rates into a compositional factor and a rate factor.

One Sentence Summary: Meaningful comparison of cross-sectional or longitudinal patenting rates requires defining a subpopulation that plausibly contributes to patenting.

Prolific Rural Inventors Raise Questions about the Geography of Invention

Abstract: Patents per capita is a widely used innovation indicator. Rural areas generally perform very poorly using this metric, suggesting that inventive activity that leads to patents is an urban phenomenon. However, newly available inventor-disambiguated patenting data demonstrate that inventions per inventor are roughly equal across urban and rural areas. A critical assessment of the patents per capita measure questions its construct validity. An alternative measure that identifies an exemplary "inventive class" and does not confound the patenting rate with irrelevant information is constructed. This allows the decomposition of overall patenting rates into a compositional factor and a rate factor.

Keywords: Patents, innovation indicators, decomposition, standardization, urban-rural comparisons.

JEL Classifications: O31, J10, O18, R11

Introduction

Conventional wisdom holds that innovation and invention are predominantly urban phenomena—concentrated most heavily in global city agglomerations—and rare or idiosyncratic in rural areas (Carlino and Kerr 2014, World Bank 2009). Patents per capita rates are highest in urban areas; however, recently available data that track individual inventors and their locations provides evidence that seemingly contradicts this wisdom: patenting rates per inventor in rural areas are roughly equal to those of urban areas. These prolific rural inventors raise important questions about the geography of invention: Does the productivity of individual inventors inform the patent production capacity of a region? If the selection of successful inventors biases the measure of regional patenting productivity, then what is the appropriate pool of potential inventors and auxiliaries who support the patenting process? Is the convention of using population as this pool defensible?

Making sense of these seemingly incongruous data compelled a critical examination of population as the default denominator for computing patenting rates. Despite the import attached to patents per capita as a primary indicator of a region's innovative capacity (Furman, Porter and Stern 2002; Carlino, et al. 2007; Krammer 2009; Galindo-Rueda 2013; OECD 2009; OECD 2010), we were unable to find any studies that confirm the validity of the construct.[i] It is somewhat ironic that a primary indicator of a region's ability to codify new ways of thinking relies on a convention of convenience. We hope to demonstrate that a meaningful comparison of cross-sectional or longitudinal patenting rates requires defining a subpopulation that plausibly contributes to patenting.

We begin by evaluating the default metrics for regional innovation/invention—patents per capita and patents per inventor—to motivate our assessment of population as a denominator and the need to search for an alternative. The fact that the patents per capita data comport with a dominant mental map of what innovation data should look like demands an explanation of why. The portfolio of places argument in the World Bank's Reshaping Economic Geography (2009) provides a rational explanation that relegates lower order places to filling more routine production, service, and logistical roles. This compels the disturbing follow-on question: Why is there any patenting in rural areas?

This leads us to an inductive identification of the regional inventive economy that provides an alternative basis for assessing the relative patenting productivity of a region by allowing us to compute patenting rates on the subset of the population who might plausibly contribute to patent production. The competing measures are compared axiomatically and empirically to assess their relative construct validity. A method for decomposing the population denominated patenting rate into a compositional factor pertaining to the inventive class and a rate factor provides new insights on patent indicators, stimulating further debate on this important topic.

Inventor Disambiguated Patent Data

This analysis uses a novel database covering all utility patents granted by the U.S. Patent and Trademark Office from 1975 through 2010. It was constructed from a new data product, supported in part by the National Science Foundation, which uses a Bayesian supervised learning approach to uniquely identify all inventors that appear on utility patents (Lai, et al. 2013). This means that inventors can be located and tracked across space and time. Using the USGS Geographic Names Information System, we assign each inventor to a county based upon the city and state of the inventor's address provided at the date of patent application. For patents with more than one inventor, we assign each author an equal fraction of that patent. County identifiers associated with individual patents allow us to construct a consistent dynamic profile of rural patenting, rural inventors, and rural technologies (reference redacted to maintain anonymity).

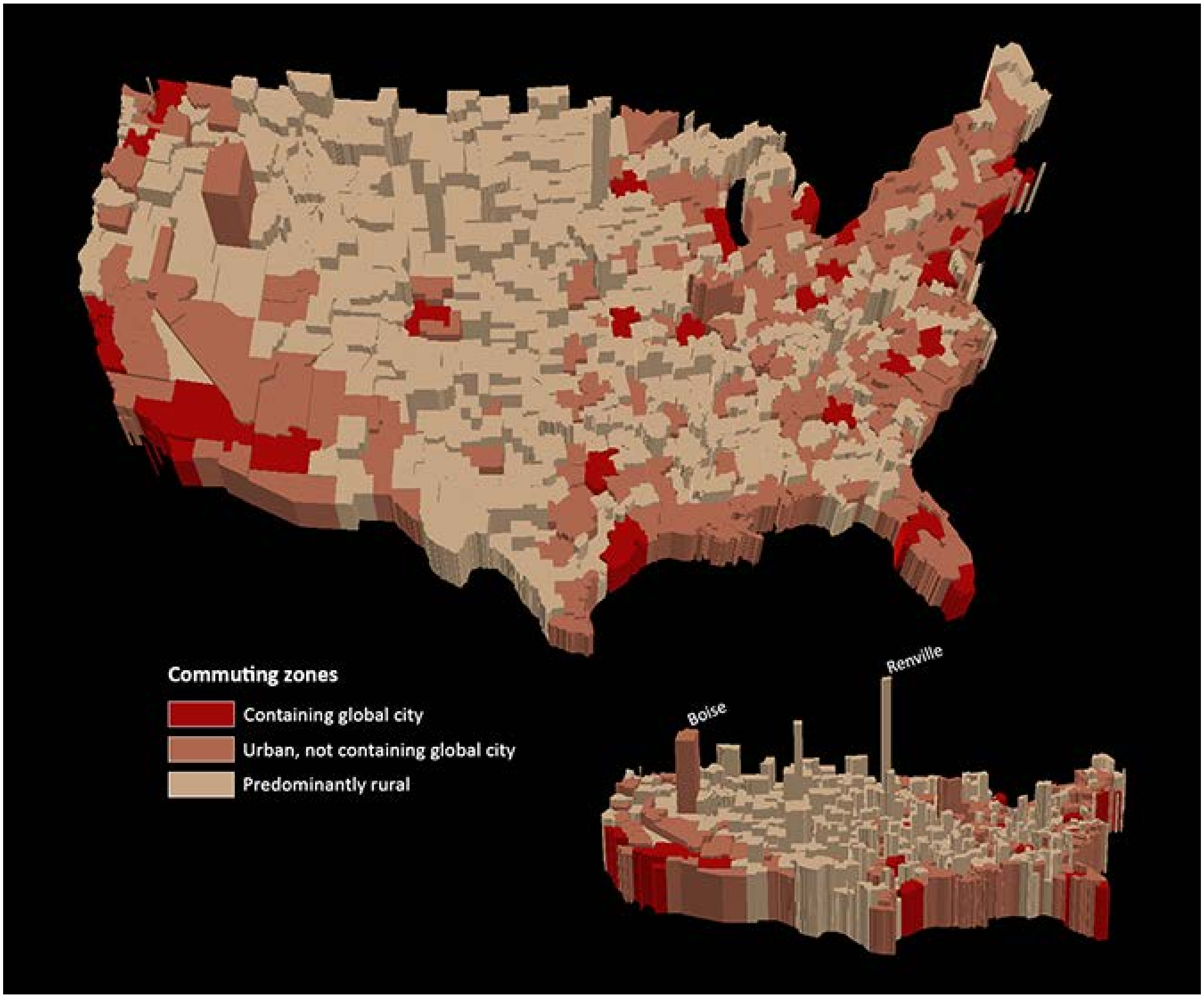
County level patent data may suffer from false precision, as place of invention is defined by the inventor's place of residence, which may differ from the county where much of the inventive work took place. This is especially likely in large urban agglomerations. To address this problem, our analysis uses a commuting zone geography that aggregates counties based on the strength of inter-county commuting patterns (Parker 2012). While this strategy cannot guarantee the reported patent statistics resolve all place of work versus place of residence discrepancies, it should resolve the great majority of them.

What the Data Show

Patents per capita purports that a region's entire population – very young to very old, white collar and blue collar, employees in industrial and service sectors – possess equal patenting capacity. Using patents per inventor restricts the plausible patenting population to those who have achieved patenting success.

Patenting rates per inventor are displayed as the third dimension in Figure 1.

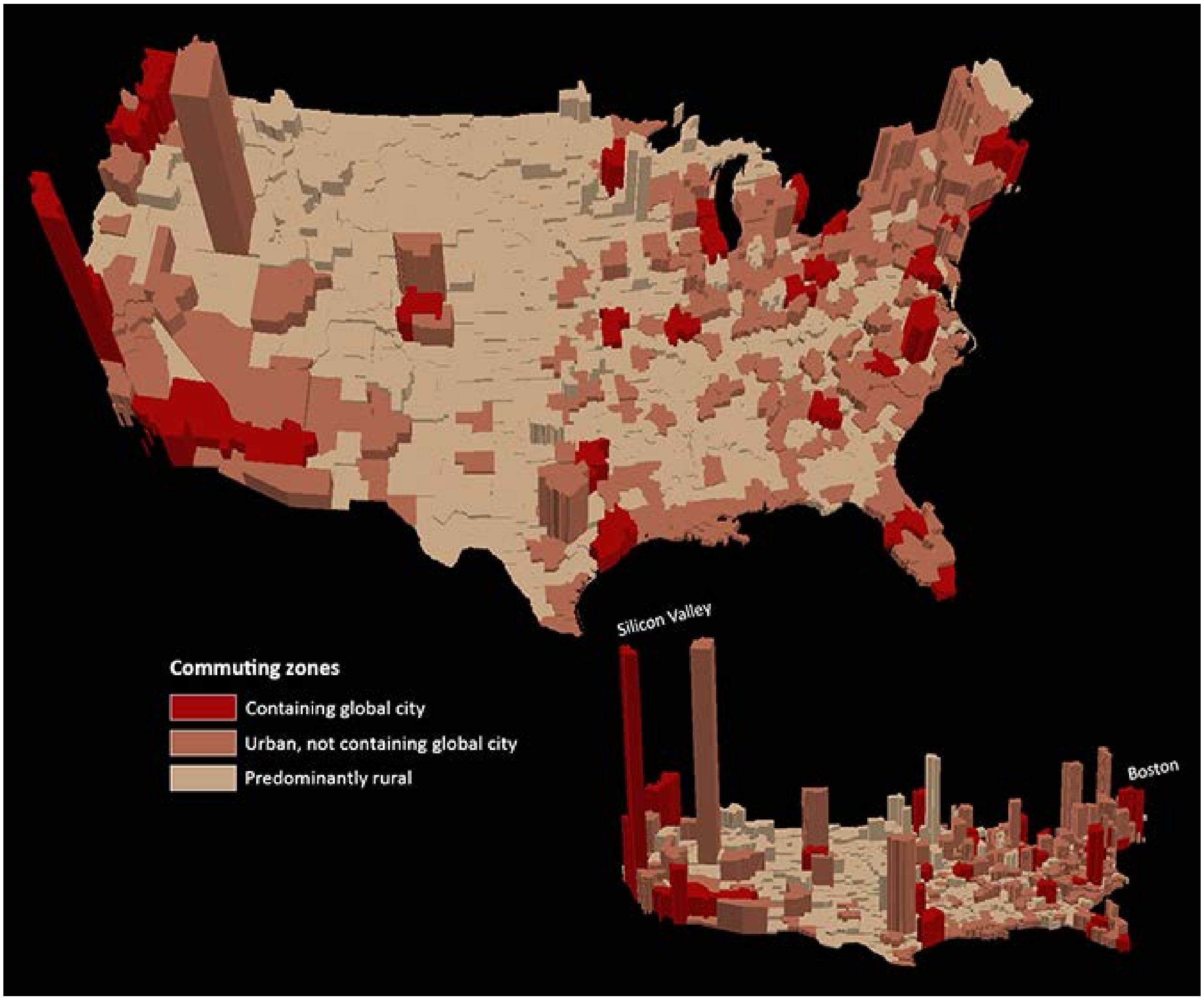
Figure 1. Patents per inventor, 2000-2005, by commuting zone



Commuting zones are identified as either containing a global city, urban without a global city, or predominantly rural.[ii] The image is disconcerting for those well-versed in the geography of invention (or as confounded with the geography of innovation), as the anticipated red peaks of invention in well-known global cities and the ivory valleys of rare rural and small city invention are replaced by an eerily uniform distribution of inventiveness. The two exceptions are the counties of Redwood and Renville in Minnesota and the Boise, Idaho, commuting zone. Redwood-Renville counties stand out as a singular case where the inventive process is prominent and exalted in a rural community—it is the home of the Minnesota Inventors Hall of Fame and actively supports student inventors. Boise provides a more conventional story of the geographic concentration of patents—since the 1970s it has developed as a satellite of Silicon Valley (Mayer 2009). A transplanted Hewlett-Packard facility, homegrown Micron Technology, and a growing number of high-tech firms have relied heavily on quality-of-life amenities to attract highly skilled labor. Aside from these two cases, this map suggests that the projection of an individual measure of productivity to a geographical area may be a poor representation of the area's inventive capacity.

Indeed, the selection of inventors as the denominator may raise valid questions about models of the inventive process, supporting strong priors that patents per inventor should be higher in global cities. But the measure does not inform the inventive capability of a place. Having selected successful inventors for the metric, it may represent nothing more than a quantification of anecdotal evidence of the rare rural inventor. Patenting rates calculated on a per capita basis applied to these data restore confidence in our priors on the geography of invention.

Figure 2. Patents per capita, 2000-2005, by commuting zone



In Figure 2, the Silicon Valley commuting zone containing San Jose is returned to its point of prominence, while patenting in Boston, though reasonably high, is eclipsed by other Northeastern urban areas. Although the map does not support a strict dominance of global city commuting zones over other urban commuting zones, it does clearly indicate that patenting in rural commuting zones is muted. However, the challenge to one denominator should extend to the other even if the map of the metric comports with our priors.

The validity of population as the denominator for computing patenting rates is best challenged by a thought experiment of industrial clustering run amok. Say that alongside nanotechnology cities, biotechnology cities, and software cities we had retirement cities and tourism cities. Comparing patenting rates across these two groups based on population would be wholly uninteresting. Yet, in the real world, some places may have a substantial portion of their population supported by economic activities that have exceedingly low patenting rates. So should the patenting rate of Paris take a hit just because it also happens to be the leading tourism destination in the world? Tourism in Paris arguably supports a more vibrant café economy and such places may be an essential component of the invention ecosystem. If tourism employment is generally associated with higher patenting rates, we will have learned something and opened up new questions about the inventive process. If not, we should stop penalizing the patenting rates of beautiful places.

This same plea applies to much less notable places characterized by a concentration of essential economic activities with exceedingly low patenting rates. The production of food and fiber in rural areas is the most obvious example. The World Bank's report on Reshaping Economic Geography provides a convenient oversimplification that allocates the whole of the innovation economy, where invention is presumed to take place, to the largest cities:

> Research over the last generation indicates that different forms of human settlement facilitate agglomeration economies for different forms of production. A somewhat-oversimplified (but not altogether incorrect) generalization would be that market towns facilitate scale economies in marketing and distributing agricultural produce, medium-size cities provide localization economies for manufacturing industries, and the largest cities provide diverse facilities and foster innovation in business, government, and education services (2009, p. 128).

A more nuanced view of the World Bank report would acknowledge that small parts of the innovation economy may locate in some rural areas. From this perspective, both maps above distort the true inventive capacity of places.

An Inductive Approach for Identifying the Inventive Class

The essential problem is how one defines an exemplary population for evaluating the inventive productiveness of a region. In the absence of a single compelling alternative, total population has been uncritically accepted as the valid default measure. Since indicators using population as the denominator comport with where conventional wisdom expects inventive productiveness to be highest there has been no reason to challenge its adequacy. However, the thought experiment above demonstrates why this is a weak construct for assessing inventive productiveness. Since “it is not obvious what the appropriate set of occupations should be” (Carlino et al. p. 404) the absence of a perfect denominator has dispelled the need to look for a much better denominator. Our goal is to begin this search for a better denominator that represents an inventive class that does not dilute the contribution of the part of the economy that plausibly contributes to patenting.[iii]

We attempted to identify an inventive class using the inclusive 24 summary occupations in the U.S. Census Bureau’s American Community Survey. This attempt led to two findings: (1) the only occupations consistently associated with patenting are members of Richard Florida’s “creative class,” described as professions that generate “new ideas, technology, and/or creative content” (Florida 2002, p. 8); and (2) some summary creative class occupations never associated with patenting contain detailed occupations one would expect to be (e.g., Postsecondary Teachers in the Education and Library Occupations category, i.e., college professors).

This led us to limit the candidates for our inventive class to employees of the detailed 109 creative class occupations.[iv] At the root of our analysis is a simple linear regression of 2000-2005 county-level patent totals ($\mathrm{Patents}$) on the share of the county’s workforce in each occupation (OccS) and 2003 Rural-Urban Continuum (Beale) Code fixed effects (γ). To mitigate effects of collinearity between occupation shares, we randomly select 20 occupation shares to include in each of 10,000 separate regressions (Equation 1).

Equation 1

$$Patents = \beta_0 + \beta_1 OccS_1 + \cdots + \beta_{20} OccS_{20} + \gamma + \varepsilon$$

Following each regression, we update a collection of count variables which record instances of inclusion for each occupation share as well as whether each occupation share coefficient is positive and significant at the 10% level. These measures allow us to calculate the percentage of time a particular occupation share effect is positive and significant in the iterative regression analysis. To account for differences in composition of inventive class in metropolitan and non-metropolitan areas, we separately analyze metro and non-metro counties.

Our inventive subset inclusion criteria are as follows. Occupations associated with coefficients that are positive and significant in at least 75% of their regressions in the metro or non-metro analysis are characterized as inventive. We additionally include occupations associated with positive and significant coefficients in at least 50% of their regressions in the metro and non-metro analysis in our inventive subset to capture inventive processes that appear to be widespread, if not clearly defined. Of the 109 creative class occupations included in the analysis, we identify 42 as "inventive" (Table 1).

Table 1. Inventive occupations

Occupation	Percent positive and significant[1]	
	Metro.	Non-metro.
Marketing and sales managers	85.46	100.00
Computer and information systems managers	73.36	94.24
Industrial production managers	0.00	95.21
Architectural and engineering managers	86.51	100.00
Miscellaneous managers, including funeral service managers and postmasters and mail superintendents	13.05	94.45
Accountants and auditors	81.82	100.00
Computer and information research scientists	60.75	53.17
Computer systems analysts	12.65	97.41
Computer programmers	53.20	100.00
Software developers, applications and systems software	100.00	100.00
Web developers	80.83	37.09
Computer support specialists	29.44	95.99
Network and computer systems administrators	0.78	93.68
Computer network architects	1.45	99.64
Computer occupations, all other	0.00	96.08
Actuaries	2.86	99.15
Architects, except naval	82.96	100.00
Aerospace engineers	80.32	0.00
Biomedical engineers and agricultural engineers	9.90	100.00
Chemical engineers	0.00	100.00
Computer hardware engineers	100.00	37.24
Electrical and electronics engineers	100.00	66.41
Industrial engineers, including health and safety	41.58	100.00
Materials engineers	59.15	100.00
Mechanical engineers	23.76	100.00
Miscellaneous engineers, including nuclear engineers	83.63	94.45
Drafters	0.00	88.87
Medical scientists and life scientists, all others	98.25	100.00
Astronomers and physicists	0.10	82.40
Chemists and materials scientists	45.46	100.00
Physical scientists, all other	85.21	100.00
Psychologists	57.42	99.19
Lawyers	82.37	69.10
Postsecondary teachers	1.09	92.90
Designers	99.85	100.00
Actors	99.80	0.00
Producers and directors	88.37	0.00
Public relations specialists	1.75	79.26
Technical writers	76.75	67.55
Television, video, and motion picture camera operators and editors	84.84	1.54
Sales representatives, wholesale and manufacturing	4.16	100.00

Note: [1] At 10% level
Source: Census Bureau

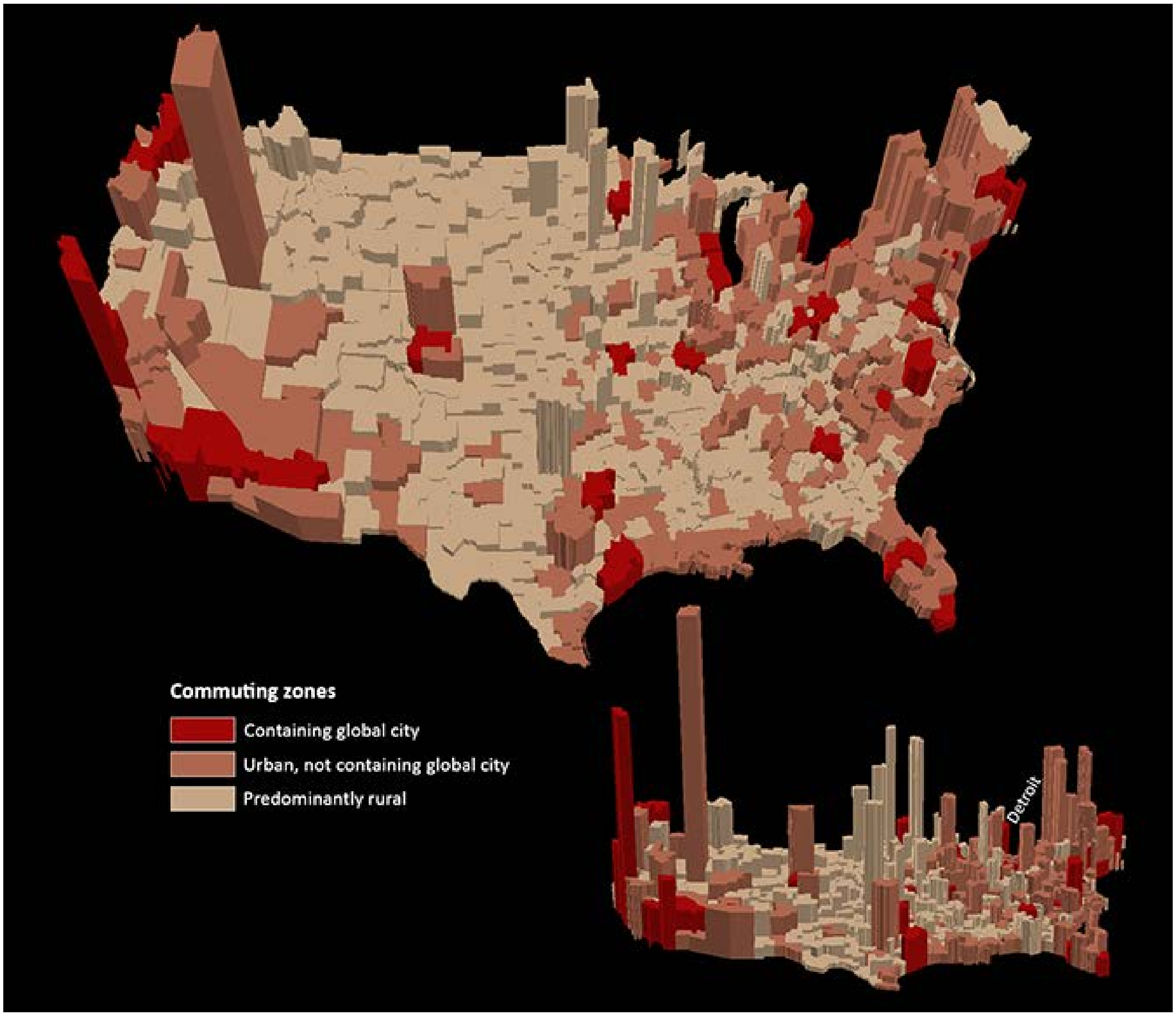
Occupations that fail to “make the cut” include construction managers, first-line supervisors of retail sales workers, and operations research analysts, which are all associated with consistently negative effects in metro areas. Many occupations not traditionally associated with inventiveness are eliminated, including telemarketers, food service managers, and travel agents. A number of natural and social science occupations such as atmospheric and space scientists, agricultural and food scientists, and economists are excluded from the inventive subset.

The group of inventive occupations includes some detailed manager occupations, computer science professionals, engineers, natural scientists, and designers. Also included are lawyers who may contribute to inventiveness of the county population indirectly by providing legal counsel. Psychologists are also consistently associated with patenting, but the reason for this is not immediately clear. As with Actors, and Producer and Directors, these occupations may be indicators of highly inventive environments even if they are not directly involved in the patenting process. Our inductive approach does not allow excluding occupations that lack a strong conceptual connection to inventing.

Comparing Patenting Rates Denominated by Population and Inventive Class

The topography of the geography of invention in the patents per capita map is retained in Figure 3 but with a higher base plateau throughout and numerous eruptions of predominantly rural commuting zones. The map directly challenges the characterization of rural inventing as idiosyncratic and muted.

Figure 3. Patents per inventive class member, 2000-2005, by commuting zone



To examine the validity of the alternative measures of inventive activity more fully, we adopt the axiomatic approach to indicators made famous by Sen's (1976) assessment of alternative poverty measures. Axiomatically, both patents per capita and patents per inventive class member will show an increase in patenting rate with a decline in the relevant denominator, *ceteris paribus*. In the case of patents per capita a decline in population tells us nothing about the change in the inventive productiveness of a region. In the patents per inventive class member case, however, a decline in a region's inventive class, *ceteris paribus*, signifies an increase in its inventive productiveness, as fewer potential inventors and their auxiliaries are producing the same number of patents.

The complex process surrounding population growth ensures that the *ceteris paribus* condition will rarely hold. Table 2 provides the information needed to compare patenting rates, population growth and employment shares across global city commuting zones. From the axiomatic critique, we would expect the rankings of those global city commuting zones experiencing a relative population decline to fall in rank moving from the per capita measure to the alternative inventive class measure. In fact, the Philadelphia commuting zone is the only low growth global city commuting zone (population growth less than 10% from 1975 to 2000) demonstrating a fall in rank. Cleveland, the global city commuting zone that had the largest population decline, also demonstrates the largest increase in rank when shifting from the per capita measure to the inventive class measure. Other global cities more associated with the declining Rust Belt than with innovative capacity such as Detroit and Milwaukee also rise in rank using the alternative measure.

Table 2. Patenting statistics for commuting zones containing global cities

Patents per capita rank	Global city commuting zone	Patents per capita	Patents per inventive class member	Patents per inventive class member rank	Change in rank[1]	Population growth, 1975-2000	Manufacturing employment share	Tradable services employment share	Inventive class employment share
1	San Jose, CA	0.02165	0.19103	1	0	45.90%	0.228	0.280	0.230
2	San Francisco, CA	0.00614	0.06523	2	0	38.44%	0.103	0.344	0.183
3	Portland, OR	0.00538	0.06414	3	0	62.25%	0.164	0.285	0.151
4	Minneapolis, MN	0.00523	0.05301	5	-1	40.58%	0.151	0.332	0.171
5	Raleigh, NC	0.00518	0.04794	9	-4	83.77%	0.178	0.256	0.174
6	Seattle, WA	0.00514	0.05188	6	0	65.93%	0.148	0.309	0.177
7	San Diego, CA	0.00492	0.06345	4	3	74.86%	0.119	0.279	0.158
8	Boston, MA	0.00467	0.05037	8	0	11.20%	0.127	0.323	0.177
9	Denver, CO	0.00315	0.03204	16	-7	69.69%	0.090	0.361	0.169
10	**Detroit, MI**	**0.00312**	**0.05103**	**7**	**3**	**1.50%**	0.198	0.280	0.147
11	Dallas, TX	0.00309	0.03870	11	0	79.46%	0.134	0.342	0.142
12	**Philadelphia, PA**	**0.00246**	**0.03298**	**15**	**-3**	**3.09%**	0.122	0.295	0.153
13	Phoenix, AZ	0.00241	0.03356	13	0	142.65%	0.110	0.277	0.126
14	Houston, TX	0.00233	0.03022	18	-4	81.15%	0.121	0.276	0.132
15	Cincinnati, OH	0.00232	0.03415	12	3	17.49%	0.160	0.288	0.134
16	**Cleveland, OH**	**0.00232**	**0.03918**	**10**	**6**	**-3.02%**	0.191	0.266	0.129
17	**Milwaukee, WI**	**0.00228**	**0.03310**	**14**	**3**	**8.64%**	0.221	0.256	0.135
18	Chicago, IL	0.00202	0.02837	19	-1	15.42%	0.156	0.321	0.143
19	Los Angeles, CA	0.00201	0.03172	17	2	55.89%	0.161	0.300	0.130
20	Atlanta, GA	0.00198	0.02155	21	-1	102.81%	0.087	0.381	0.157
21	Washington, DC	0.00188	0.01435	28	-7	39.83%	0.032	0.373	0.216
22	Baltimore, MD	0.00156	0.01841	23	-1	16.34%	0.092	0.276	0.161
23	St. Louis, MO	0.00147	0.02171	20	3	8.66%	0.135	0.302	0.135
24	Kansas City, MO	0.00147	0.01922	22	2	26.07%	0.107	0.357	0.138
25	Columbus, OH	0.00130	0.01679	25	0	27.95%	0.134	0.291	0.141
26	Miami, FL	0.00127	0.01795	24	2	140.73%	0.063	0.307	0.116
27	Charlotte, NC	0.00098	0.01313	30	-3	58.68%	0.187	0.311	0.126
28	Tampa, FL	0.00095	0.01586	26	2	68.60%	0.078	0.274	0.116
29	Orlando, FL	0.00088	0.01579	27	2	63.80%	0.067	0.313	0.110
30	New York, NY	0.00087	0.01378	29	1	6.86%	0.062	0.359	0.132

Note: [1] Denotes difference between "Patents per capita rank" and "Patents per inventive class member rank"

Source: Redacted to maintain anonymity; Census Bureau; Bureau of Labor Statistics Quarterly Census of Employment and Wages; and Special Tabulation of the 2007-2011 Pooled American Community Survey

The characteristics that these declining Rust Belt cities share is a historic dependence on manufacturing, which might help explain the relatively higher patenting productivity of their inventive class. Based on evidence from 2008, most patent applications still come from manufacturing (69.5% of all patent applications in 2008), with industries in chemicals (13%), and computer and electronic products (29.9%), accounting for the bulk of all patent applications (Shackelford, 2013). Patenting in tradable services (25.7%) is less prevalent but still an important component of patent production (Shackelford, 2013). At the other end of the scale, patenting is relatively rare in nontradable services and in resource extraction (4.7%; Shackelford, 2013). From this set of facts, we would reasonably expect employment shares in manufacturing and tradable services to be associated with higher patenting rates. Table 3 provides a set of regressions to test this conjecture for patenting rates denominated by population and by inventive class, respectively.

Table 3. Regression of industry shares on alternative patenting rates

Variable	Coefficient	Standard Error
Patents per capita, 2000-2005		
Manufacturing employment share, 2000	0.0015**	0.0003
Tradable services employment share, 2000	0.0084**	0.0006
Natural resources employment share, 2000	-0.0034**	0.0006
Patents per inventive class member, 2000-2005		
Manufacturing employment share, 2000	0.0335**	0.0045
Tradable services employment share, 2000	0.0274**	0.0071
Natural resources employment share, 2000	-0.0391**	0.0081

Note: Significance levels: **1%, *5%; Nontradable services employment share is excluded.
Source: Redacted to maintain anonymity and Census Bureau

Qualitatively, both measures perform consistently with conjectures. The major difference between the two measures is the magnitude of the manufacturing share coefficient estimate relative to the tradable services coefficient estimate. The patents per capita measure gives much more weight to tradable services in explaining differences in patenting rates relative to manufacturing, and the differences in the coefficient estimates are statistically significant. In contrast, the coefficient estimates for tradable services and manufacturing employment shares in the patents per inventive class member equation are not statistically different. It is reasonable to posit that patenting rates may be dependent either on economic dynamism or a history of manufacturing specialization.

By relying on a per capita measure, patenting rates will be unable to isolate these independent contributions.

Making sense of conventional patenting rates is a challenge, as it assumes that patents emerge from a region's 'black box'—in which input factors are transformed into output—where a region's population defines the relevant measure of input. Because the process of invention is not well understood, the metaphor of the black box appears to be as good as any. Compare this with a process that is well understood, such as childbirth. The fertility of a region using the black box metaphor would simply be the number of live births in the region divided by its population. Fertility would decline with an improvement in life expectancy and would increase with a relative decline in the young or elderly populations. By defining regional fertility as a product of these rate and compositional factors, respectively, demographers and public health analysts have the ability to compare fertility across regions with different compositions and to analyze the fertility of a single region through time as its composition changes.

The same tools of standardization and decomposition are available for the study of patenting activity, as measured by patents per capita, if an inventive class is defined. The composition investigated here was derived inductively based on occupations that have a strong statistical association with patenting. Patenting rates computed using the inventive class as the denominator provides our rate factor, whereas inventive class as a share of total population provides our compositional factor (Equation 2):

Equation 2

$$\text{Patents per capita} = \frac{\text{Patents}}{\text{Inventive class}} \cdot \frac{\text{Inventive class}}{\text{Total population}}$$

Standardization tells us what observed patenting rates across populations would be if their rate (compositional) factors were identical, while decomposition answers how much of the difference in the observed patenting rates across populations can be attributed to differences in their rate (compositional) factors. Thus, by standardizing and decomposing patenting rates, we can determine how much of the difference in the population denominated patenting rate across populations is attributable to differences in patenting productivity of the inventive class and how much is attributable to differences in the proportion of the inventive class as a share of total population.

Suppose we have two populations, i and j, and two factors, ∝ and β. Following Das Gupta (1993), let the observed patenting rate of population k be expressed as

$$R_k = \alpha_k \beta_k$$

Then, for $k \in \{i, j\}$, the α-standardized rate for population k is

$$\frac{\beta_i + \beta_j}{2} \alpha_k$$

while the β-standardized rate for population k is

$$\frac{\alpha_{i+} \alpha_j}{2} \beta_k$$

Factor effects for α and β are defined as the difference in β-standardized and α-standardized rates for populations i and j, respectively.

We begin by comparing the global city commuting zones that maintain a relatively high share of manufacturing employment (i.e., share of total employment in manufacturing exceeds global city median) to those that do not. The first three rows of Table 4 show the standardization and decomposition analysis for these two populations. First, comparing patenting under the assumption that both populations had identical patenting productivity (first row of Table 4) indicates that global cities with low manufacturing shares would have higher patenting due to their composition than was actually observed (the observed rate is listed in the third row) and also higher than high manufacturing share global cities. Comparing patenting under the assumption that both populations had identical compositions (second row of Table 4) indicates that inventive class productivity in global cities with low manufacturing shares would have lower patenting than was actually observed and still lower patenting than high manufacturing share global cities. This suggests global cities with low manufacturing shares had a compositional advantage that was more than offset by a patenting productivity disadvantage within the inventive class.

Table 4. Standardization and decomposition of patenting rates comparing global city commuting zones based on manufacturing dependence

Measures	Standardization		Decomposition	
High and low manufacturing share global city CZs	High mfg share	Low mfg share	Difference (effects)	Percent distribution of effects
Rate factor-standardized patenting rate	0.00288	0.00313	-0.00025 (CF-effect)	-24.6136
Compositional factor-standardized patenting rate	0.00365	0.00237	0.00128 (RF-effect)	124.6136
Observed patenting rate	0.00349	0.00247		

Source: Redacted to maintain anonymity

Next, we extend the standardization and decomposition analysis to a comparison of global city and predominately rural commuting zones. As seen in the last column of Table 5, when applied to the two populations defined by global city and predominantly rural commuting zone status, nearly 54% of the difference in population denominated patenting rates can be attributed to differences in the regional composition. Instead of global cities being roughly five times more productive (0.00297/0.00065) than predominantly rural areas in producing patents, we see that when we hold inventive class population share constant, global cities are only twice as productive (0.00214/0.00107). That the new approach does not change the qualitative verdict that global cities are more inventive than predominantly rural areas suggests that Figure 1 is not a good representation of the regional capacity for patentable innovation. However, the large difference between the compositional factor-standardized patenting rate and the observed patenting rate suggests that Figure 2 may also mislead. Contrary to being a matter of type where large cities support invention and smaller places generally do not, geography of invention is seemingly a matter of degree.

Table 5. Standardization and decomposition of patenting rates comparing global city and predominantly rural commuting zones

Measures	Standardization		Decomposition	
Global city and predominantly rural CZs	Global city	Predominately rural	Difference (effects)	Percent distribution of effects
Rate factor-standardized patenting rate	0.00223	0.00098	0.00125 (CF-effect)	53.7865
Compositional factor-standardized patenting rate	0.00214	0.00107	0.00107 (RF-effect)	46.2135
Observed patenting rate	0.00297	0.00065		

Source: Redacted to maintain anonymity

Discussion

Despite their widespread use, patents per capita have not been sanctified as official statistics for regional invention by national statistical agencies. Substantial efforts at the international level to harmonize patent statistics for cross-national comparisons provide strong evidence of the importance attached to these innovation indicators (Galindo-Rueda 2013, OECD 2009*)*. Yet, the most recent review of the value of patent statistics is agnostic (National Research Council 2014, p. 5-9):

> The panel makes no explicit recommendation here for NCSES [National Science Foundation's National Center for Science and Engineering Statistics] to do more than continue to explore wider use of patent indicators and to engage in international cooperation on the development of indicators based on patent records to address user needs. There is no standard method for calculating indicators from patent data, and as noted earlier, analysis of these data without reservation can lead to incorrect inferences and misleading policy decisions….As NCSES continues to disseminate patent data as part of its STI indicators program, it would be valuable to users to have clear cautions regarding the use and misuse of these statistics for decision-making purposes.

The central purpose of this paper is to demonstrate that meaningful comparison of cross-sectional or longitudinal patent rates requires defining a subpopulation that plausibly contributes to patenting. The inductive identification of an inventive population or inventive class allows computing patenting rates on an exemplary population, where patenting productivity is not confounded by population irrelevant to the patenting process. Separating the simple population patenting rate into a compositional factor and a rate factor introduces the concepts of standardization and decomposition that have been essential for meaningful cross-sectional and longitudinal comparisons of demographic phenomena. The importance of this method to the innovation literature is best expressed in the title of the National Research Council report: Capturing Change in Science, Technology, and Innovation: Improving Indicators to Inform Policy.

The main take away from this analysis regarding the geography of invention is that rural patenting rates denominated by the inventive class are half the patenting rates of global cities in the US, on average. At the individual commuting zone level, 8% of predominantly rural commuting zones have patenting rates higher than half of the global cities. The claim that patenting is overwhelmingly an urban phenomenon, based on evidence produced from conventional patenting rates, dichotomizes the innovation economy. That dichotomization is likely to contribute to suboptimal innovation policy, as it mischaracterizes the large potential contribution from rural inventing.

Shifting from an “inventive places of type” to an “inventive places of degree” perspective may hold little sway for many innovation researchers who will still claim that most inventive activity occurs in global cities. We are not worried that studying patenting and innovation in global cities will be reduced by the confirmation that a substantial amount of invention takes place elsewhere. What is more troubling are the simple linear notions of the mindset that contends that capturing the bulk of a phenomenon is all that should matter or that promoting a phenomenon only where it is most prevalent is the most efficient strategy. This linear view is best challenged by the fact that some of the most reliable patent producers today are located in a place thought better suited to growing apricots 60 years ago.

References and Notes

Beaverstock, J. V., Taylor, P. J., & Smith, R. G. (1999). A roster of world cities. *Cities* 16, 445–458,

Carlino, G. & Kerr, W. R. (2014). Agglomeration and Innovation (Working Paper No. 20367). Retrieved from National Bureau of Economic Research website: http://www.nber.org/papers/w20367.

Carlino, G.A., Chatterjee, S., Hunt, R.M. (2007). Urban density and the rate of invention. *Journal of Urban Economics* **61**, 389-419.

Das Gupta, P. (1993). *Standardization and Decomposition of Rates: A User's Manual* Current Population Reports Special Studies P23-186. Washington, DC: Bureau of the Census.

Florida, R. (2002). *The Rise of the Creative Class: And How It's Transforming Work, Leisure, Community, and Everyday Life.* New York: Basic Books.

Furman, J.L., Porter,M.E., Stern,S. (2002). The determinants of national innovative capacity. *Research Policy* 31:899–933.

Galindo-Rueda, F. (2013). The OECD measurement agenda for innovation. In F. Gault (Ed.), *Handbook of Innovation Indicators and Measurement* Krammer, S.M.S. (2009). Drivers of national innovation in transition: Evidence from a panel of Eastern European countries. *Research Policy* 38:845‑860.

Lai, R., D'Amour, A., Yu, A., Sun, Y., Fleming, L. (2013).Disambiguation and Co-authorship Networks of the U.S. Patent Inventor Database (1975-2010) (Harvard Dataverse Network [Distributor] V5, 2013, hdl.handle.net/1902.1/15705 UNF:5:RqsI3LsQEYLHkkg5jG/jRg==).

Mayer, H. (2009) *Bootstrapping High-Tech: Evidence from Three Emerging High Technology Metropolitan Areas*, Metro Economy Series for the Metropolitan Policy Program at Brookings. Washington: Brookings Institution. Retrieved from http://www.brookings.edu/~/media/research/files/reports/2009/6/metro%20hightech%20mayer/06_metro_hightech_mayer.pdf on September 19, 2014.

McGranahan, D., & Wojan, T. (2007). Recasting the Creative Class to Examine Growth Processes in Rural and Urban Counties. *Regional Studies, 41*(2), 197–216. doi:10.1080/00343400600928285

Meliciani, V. (2000) The relationship between R&D, investment and patents: a panel data analysis, *Applied Economics*, 32(11), 1429-1437, DOI: 10.1080/000368400050151502

Morel C. M., Acharya, T., Broun, D., Dangi, A., Elias, C., Ganguly, N. K., Gardner, C. A., Gupta, R. K., Haycock, J., Heher, A.D., Hotez, P.J., Kettler, H. E., Keusch, G. T., Krattiger, A. F., Kreutz, F. T., Lall, S., Lee, K., Mahoney, R., Martinez-Palomo, A., Mashelkar, R. A., Matlin, S. A., Mzimba, M., Oehler, J., Ridley, R. G., Senanayake, P., Singer, P., & Yun, M. (2005). Health innovation networks in developing countries address neglected diseases. *Science* 309 (5733), 401-404.

Motoyama, Y., Konczal, J. (2013). How can I create my favorite state ranking?: The hidden pitfalls of statistical indexes. *Journal of Applied Research in Economic Development,* 10.

National Research Council. (2014). *Capturing Change in Science, Technology, and Innovation: Improving Indicators to Inform Policy, Panel on Developing Science, Technology, and Innovation Indicators for the Future*, R. E. Litan, A. W. Wyckoff, & K. H. Fealing, Editors. Committee on National Statistics, Division of Behavioral and Social Sciences and Education, and Board on Science, Technology, and Economic Policy, Division of Policy and Global Affairs. Washington: The National Academies Press.

Organisation for Economic Co-operation and Development (2009). *OECD Patent Statistics Manual*. Paris: OECD Publications. Retrieved from http://www.oecdbookshop.org/oecd/display.asp?sf1=identifiers&st1=9789264056442 on September 10, 2014.

Organisation for Economic Co-operation and Development. (2010). *Territorial Reviews: Venice, Italy 2010*. Paris: OECD Publications. doi: 10.1787/9789264083523-en

Parker, T. (2012). USDA Economic Research Service Commuting Zones and Labor Market Areas. Retrieved from *http*://www.ers.usda.gov/data-products/commuting-zones-and-labor-market-areas.aspx on August 29, 2014.

Porter, M.E. (2011). "Cluster mapping project." Institute for Strategy and Competitiveness, Harvard Business School.

Rothwell, J., Lobo, J. Strumsky, D. &, Muro, M. (2014). *Patenting Prosperity: Invention and Economic Performance in the United States and Its Metropolitan Areas.* Metropolitan Policy Program at Brookings Research report. Washington: Brookings Institution. Retrieved from http://www.brookings.edu/research/reports/2013/02/patenting-prosperity-rothwell August 28, 2014.

Sen, A. (1976). Poverty: An Ordinal Approach to Measurement. *Econometrica* 44, 219-231.

Shackelford, B. (2013). *One in Five U.S. Businesses with R&D Applied for a U.S. Patent in 2008*, National Center for Science and Engineering Statistics InfoBrief NSF-13-307. Arlington, VA: National Science Foundation.

World Bank. (2009). *World Development Report 2009: Reshaping Economic Geography*. Washington: World Bank.

.

[i] The only comment we were able to find questioning the validity of using population as a denominator addressed patenting rate indicators in developing countries: "The number of U.S. patents per capita is a common proxy used to measure the relative innovation efficiency of countries, but we believe that this computation underestimates the innovative capacity of developing countries, because it fails to detect the productivity of highly capable centers of excellence within countries with large populations" (Morel, at al. 2005, p. 401).

[ii] Determining the criteria for the smallest commuting zone classification was straightforward: commuting zones that contain only nonmetropolitan counties or commuting zones that contain only nonmetropolitan and small ex-urban counties classified as part of a Metropolitan Statistical Area are labelled as "predominantly rural." This classification corresponds to all commuting zones with populations of less than 250,000 in 2000. Commuting zones that contain cities included in the list of Global Cities constructed by Globalization and World Cities (GaWC) Research Network at Loughborough University are labelled as "commuting zones containing global city." The criteria for global city status are determined by the availability of advanced producer services essential for the global coordination of activities by multinational corporations (Beaverstock, Taylor, and Smith 1999). The remaining commuting zones make up the "commuting zones urban not containing global city" category.

[iii] Alternative denominators for computing regional patenting rates have been largely limited to employees, and R&D expenditures or R&D employees. Replacing population with a measure of employment corrects for the distortion introduced by variation in the size of the dependent population across regions or through time (Meliciani 2000; Porter 2011). Using R&D expenditures and R&D employees attempts to more narrowly define patent productivity but runs into the problem that not all patents come from R&D labs contributing to the erroneous result that R&D is supposedly most productive where R&D labs are rare. The closest previous research to the current effort is to use the size of the science and engineering workforce in the denominator (Motoyama and Konczal 2013).

[iv] The occupations used address the construct validity issues in Florida's original measure (McGranahan and Wojan 2007).