This article was downloaded by: [Canadian Research Knowledge Network] On: 27 May 2009 Access details: Access Details: [subscription number 783016864] Publisher Routledge Informa Ltd Registered in England and Wales Registered Number: 1072954 Registered office: Mortimer House, 37-41 Mortimer Street, London W1T 3JH, UK



To cite this Article Knudsen, Brian, Florida, Richard, Stolarick, Kevin and Gates, Gary(2008)'Density and Creativity in U.S. Regions', Annals of the Association of American Geographers, 98:2,461 — 478

To link to this Article: DOI: 10.1080/00045600701851150

URL: http://dx.doi.org/10.1080/00045600701851150

# PLEASE SCROLL DOWN FOR ARTICLE

Full terms and conditions of use: http://www.informaworld.com/terms-and-conditions-of-access.pdf

This article may be used for research, teaching and private study purposes. Any substantial or systematic reproduction, re-distribution, re-selling, loan or sub-licensing, systematic supply or distribution in any form to anyone is expressly forbidden.

The publisher does not give any warranty express or implied or make any representation that the contents will be complete or accurate or up to date. The accuracy of any instructions, formulae and drug doses should be independently verified with primary sources. The publisher shall not be liable for any loss, actions, claims, proceedings, demand or costs or damages whatsoever or howsoever caused arising directly or indirectly in connection with or arising out of the use of this material.

# Density and Creativity in U.S. Regions

Brian Knudsen,\* Richard Florida,<sup>†</sup> Kevin Stolarick,<sup>†</sup> and Gary Gates<sup>‡</sup>

\*H. John Heinz III School of Public Policy and Management, Carnegie Mellon University <sup>†</sup>Martin Prosperity Institute, Rotman School of Management, University of Toronto <sup>‡</sup>The Williams Institute, School of Law, University of California at Los Angeles

Geographers and social scientists have probed the effects of agglomeration and spatial clustering on innovation and economic growth. Economists and others have identified the role of knowledge spillovers in driving the innovation process. Although innovation is thus assumed to be a function of proximity, there has been little systematic research on the role of density in innovation. This research investigates density, and more specifically the density of creative workers, as a key factor influencing regional innovation. It uses principal components analysis to create and implement a composite measure of density and presents a model of innovation as a function of creative density. Statistical analyses including multivariate regression find that density and creativity separately and jointly affect innovation in metropolitan areas. The regression analysis finds a positive relationship between the density of creative workers and metropolitan patenting activity, suggesting that density is a key component of knowledge spillovers and a key component of innovation. *Key Words: creativity, density, innovation, metropolitan areas, spillovers.* 

地理学家和社会科学家们已经摸索出集聚和空间聚类对创新和经济增长的影响。经济学家和其他学者已确定知识外溢在推动创新的过程所扮演的角色。虽然创新被假设为一个邻近的函数,但没有足够的系统研究来确定密度在创新上起着的作用。本研究调查密度,更具体地说创意工作者的密度,作为影响区域创新的一个重要因素。研究采用主成分分析法来制定和实施一项综合措施的密度,并提出了一个创新的典范,作为一个创意密度的函数。统计分析法(包括多变量分析)发现,密度和创造性分别地和共同地影响都市地区的创新。此研究的回归分析发现,创作人员的密度和都市圈专利申请活动,有着正相关关系。这说明密度是知识溢出的重要组成部分,也是创新的一个关键组成部分。*关键词:创造力,密度,创新能力,大都会地区,外溢效应。* 

Los geógrafos y los científicos sociales han investigado los efectos de la aglomeración y del agrupamiento espacial en la innovación y el crecimiento económico. Los economistas y otras personas han identificado el papel del desbordamiento del conocimiento en el impulso del proceso de innovación. Aunque, por consecuencia, se supone que la innovación es función de la proximidad, se han realizado pocas investigaciones sistemáticas sobre el papel de la densidad en la innovación. En esta investigación se estudia la densidad, y más específicamente la densidad de trabajadores creativos, como un factor clave que influencia la innovación regional. Se utiliza el análisis de los componentes principales para crear e implementar una medida compuesta de la densidad, y se presenta un modelo de innovación como función de la densidad creativa. Los análisis estadísticos, que incluyen regresión múltiple, indican que la densidad y la creatividad juntas y por separado afectan la innovación en las áreas metropolitanas. El análisis de regresión muestra una relación positiva entre la densidad de trabajadores creativos y la presentación de patentes en el área metropolitana, lo cual sugiere que la densidad es un componente clave del desbordamiento de conocimiento y de la innovación. *Palabras clave: creatividad, densidad, innovación, áreas metropolitanas, desbordamiento de conocimiento*.

G eographers and social scientists have long been interested in the effects of proximity and agglomeration on innovation and economic growth. Ever since Alfred Marshall, geographers have examined the economic consequences of dense linkages in industrial and economic agglomerations. These geographic agglomerations create external economies of scale by sharing technology and managerial expertise. For the past two decades, economic geographers have been especially interested in the rise of specialized innovation districts in the innovation process. The transfer of skills and qualifications and the enhanced capacity for the acquisition of tacit knowledge by the small to medium-sized firms in these districts promotes innovation and innovation diffusion (Asheim 2000). Saxenian (1994) identifies Silicon Valley as a model industrial district with high rates of growth and innovation flowing from its dense geographic networks of technology firms. More recently, geographers and economists have focused on the role of knowledge spillovers in powering innovation. This view argues that there is a geographic boundary to the learning and transfer of knowledge between individuals and firms that precedes innovation.

Building on this past work, geographers now place innovation and knowledge creation in an increasingly spatial context. Feldman and Florida (1994, 210) suggest that "innovation is increasingly dependent on a geographically defined [technological] infrastructure." Bunnell and Coe (2001) explore "spaces of innovation," suggesting linkages and interrelationships across spatial scales. Bathelt, Malmberg, and Maskell (2004, 40) conclude that innovation and new knowledge are best understood as a combination of local and global interactions. Sonn and Storper (2003) find that inventors increasingly cite local patents over time. More recently, density has become a topic of increasing interest to scholars studying the geographic factors that influence regional innovation and growth (Ciccone and Hall 1996; Carlino, Chaterjee, and Hunt 2001, 2007; Sedgely and Elmslie 2004; Andersson, Quigley, and Wilhelmsson 2005; Strumsky, Lobo, and Fleming 2005). This work finds relationships between local or national employment density and labor productivity or patenting activity.

Innovation is a much studied topic in its own right. In her pathbreaking book The Economy of Cities, Jane Jacobs (1969, 49) connects innovation and growth when she claims that "Innovating economies expand and develop. Economies that do not add new kinds of goods and services, but continue only to repeat old work, do not expand much nor do they, by definition develop." Jacobs also corrects Adam Smith's view that specialization drives economic growth, arguing instead that diversity generates innovation. Glaeser (2000, 83) views cities as centers of idea creation and transmission and figures that "cities will grow when they are producing new ideas or when their role as intellectual centers is increasing." Romer (1990) and other new growth theorists cite innovation as a key factor in economic development. Finally, Lucas (1988) focuses on the importance for innovation of human capital externalities and the clustering of people. Thus, given the correspondence between innovation and sought social outcomes, it remains to identify the causal factors that bring about innovation.

This article builds on this recent attention and extends the existing literature on the determinants of regional innovation in a number of important ways, foremost by focusing on the relationship between innovation outcomes and the interaction of highly skilled individuals and population density. In doing so, we expand on, and in some important ways depart from, the interrelated concepts of proximity, knowledge spillovers, and face-to-face interactions of intellectual human capital often discussed in recent economic geography literature. Building on some of these recent articles, we go beyond the concept of population density by combining our use of it with the recent research demonstrating the positive effects of human capital on innovation to posit that high densities of human capital workers promote innovation. We estimate a crosssectional linear regression model over 240 geographic metropolitan areas in the United States. This analysis examines how creative density, the density of the creative class, affects patenting activity. Using principal components analysis we construct a novel composite population density measure, which we then intersect with a measure of creative-class employment. When included in a linear regression model alongside other important predictors of innovation, this creative density term is found to relate to metropolitan area patenting positively and significantly. Creativity and the composite density measure also independently relate positively to innovation.

We proceed with a concepts and theory section that first examines the existing research that to date looks into the geographical determinants of innovation, then briefly suggests how a testable theory arises from it, and subsequently examines this hypothesis in greater detail. We then discuss the data, methodologies, results, conclusions, and policy aspects of the findings.

# Concepts and Theory

### Agglomeration and Innovation

An almost century-long lineage of scholarship (Marshall 1920; Jacobs 1961, 1969; Thompson 1965; Storper 1997; Porter 1998; Scott 2000, 2005) describes the existence of agglomeration economies and their role in innovation and economic growth. Many studies have noted the tendency of high-tech industries to cluster. Others have noted the importance of industrial districts to the flow of innovation and economic growth (Piore and Sabel 1984). Saxenian (1994) examines the density of high-technology industry and the production of innovation in Silicon Valley and Boston's Route 128. Glaeser (2005) points to New York City's historical agglomerations in the garment and publishing industries and the relationship of these clusters to the city's role as the nation's premier port. He also explains that the current-day propensity of financial activity in New York stems from the need for quick access to idea flows and the most recent information. Creative industries also cluster. Caves (2002) provides an economic framework for explaining why industries producing intangibles would cluster. Currid (2006, 344) illustrates the concentration of artistic and cultural occupations in New York City, and suggests that "dense production agglomerations are especially likely to be sites of originality and inventiveness." Scott (2005, 9) describes how "Hollywood became, and continues to be, the largest and most influential cultural-product agglomeration in the world." Certainly, these different cities underwent varying processes of development, but geographic proximity and density were common factors for them all. In this article, we build on this rich scholarly historical foundation by exploring how creative density—the density of creative occupations-relates to innovation in U.S. metropolitan areas. The following sections discuss how and why urban creative density matters for the innovative processes that power economic development and growth.

## **Knowledge Spillovers**

Knowledge spillovers have been noted as a key reason for the spatial clustering of innovative industries. Demonstrating that knowledge can spill across firms at all, especially across firms in close technological proximity, means that there is a credible possibility that geographic proximity can also mediate these spillovers (Feldman 2000). A study by Audretsch and Feldman (1996) presents key findings in this recent literature that attempts to measure "the geographic impact of knowledge spillovers on innovation" (Feldman 2000, 374). They note that an important result of previous research is that the research and development (R&D) investments of private corporations and universities spill over to third parties. If the ability to receive knowledge spillovers depends on distance from the knowledge source, then clustering of knowledge-producing inputs (R&D expenditures, human capital, etc.) should ensue. It follows that innovative activity should also cluster following the clustering of the inputs. Conversely, if we observe a more evenly spread pattern of innovation, it would imply that knowledge spillovers are not geographically mediated. Audretsch and Feldman find that, even after controlling for the concentration of production, innovation is still concentrated close to

the source of the new knowledge. This provides evidence that the spillovers have a geographic limitation. This research reflects and clearly builds on early work by Feldman and Florida (1994, 210) that found that "innovation is increasingly dependent on a geographically defined [technological] infrastructure." Additionally, research by Anselin, Varga, and Acs (2000) found strong evidence of geographically mediated spillovers between university research and industrial innovation in the electronics and instruments industries. Glaeser (2000, 103) provides intuition for this effect when he notes that "The [externality] kind of [nonmarket] interaction even more strongly depends on spatial proximity. In many cases, these effortless transmissions of ideas and values depend on sight or hearing. . . . Obviously, the ability to see or hear depreciates sharply with space." Research in this vein shows that geographic proximity of knowledge-producing inputs influences the knowledge flows that are responsible for innovation. Yet, attention is given neither to the mechanisms producing the spillovers nor to specific conceptions of proximity like density. We next discuss such mechanisms.

Zucker, Darby, and Brewer (1998) demonstrate how intellectual human capital is a means by which geographically mediated spillovers are realized. They empirically demonstrate how the localization of intellectual human capital (embodied in "star" biotechnology scientists) is predictive of the localization of new biotech startup firms. Feldman (2000, 380-81) claims that "[t]his work demonstrates that localized intellectual capital is key in the development of the bio-tech industry and that knowledge generates externalities that tend to be geographically bounded within the region where the scientists reside." Thus, whereas the first strain of literature demonstrated that geographic proximity is important in that it promotes the spillovers necessary for innovation, this research suggests that the skills and knowledge embodied in individuals are the mechanisms by which these spillovers actually occur. Lucas (1988) and Storper and Venables (2004) take this one step further by reasoning that it is the faceto-face interactions between individuals with high human capital that facilitate spillovers and the growth of knowledge. Lucas continues by saying that these interactions are so important that people are willing to pay extremely high land rents to be close to other people, and thus to benefit in terms of learned knowledge and increased productivity. Pinch and Henry (1999) and Almeida and Kogut (1999) both illustrate one particular manifestation of these mechanisms. For two separate industries (the British motor sport industry

and the semiconductor industry, respectively), these two papers show that knowledge and ideas are circulated within regional boundaries through the mobility of highly skilled personnel between companies. Thus, according to this research, knowledge is transferred between people within and across firms through face-toface meetings.

#### Innovation, Density, and Creativity

In *The Economy of Cities*, Jacobs (1969) defines innovation as the process by which new work is added to old divisions of labor, thus creating new products, processes, or ideas, and also new divisions of labor. Feldman (2000, 373) adds that "innovation is the novel application of economically valuable knowledge." In other words, innovation is a process of creating new, profitable products and ideas by combining observations or insights taken from elsewhere with the work one had previously been doing (Desrochers 2001, 378).

Innovations occur when individuals with high degrees of existing creativity or knowledge make new and novel combinations of this knowledge with new insights observed or learned through spillovers. Individuals require a high degree of existing expertise to engage in innovation for a number of reasons. First, an extensive and sophisticated knowledge of the initial work will provide insights into how to create new combinations when new observations arise through spillovers. Clearly, if one has a superficial knowledge of the initial work, it will be less obvious how to make interesting departures from that work or important additions to it. Cohen and Levinthal (1994) note that this phenomenon exists at the firm level, referring to a firm's ability to leverage its installed base of expertise to sift through and take advantage of the signals it receives from the outside as the firm's "absorptive capacity." Additionally, Desrochers (2001, 376) adds that "innovation ultimately depends to some degree on one person's knowledge and skills," and Lee (2001) has empirically documented the positive effects of high human capital workers on innovation. Thus, the ideas necessary for innovation are embodied in individuals with the creativity, know-how, and skills to engage in technological advance.

As we have described, proximity is a key factor in this process of innovation. The geographic proximity of individuals possessing high levels of human capital, skills, expertise, or creative capabilities enables their interactions; these interactions in turn facilitate the spillovers necessary for innovation. To date, such a theory has not been sufficiently empirically tested in the literature except for in a recent paper using French data by Autant-Bernard (2001). Our analysis differs from theirs in that we examine metropolitan-level population density as a specific conception of geographic proximity. Recent research from a variety of disciplines has begun to explore the relationship between forms of density and the production of new knowledge. For example, at the state level, Ciccone and Hall (1996) find that employment density increases average labor productivity, and Sedgely and Elmslie (2004) find a positive relationship between state population density and innovation. At the city level, Strumsky, Lobo, and Fleming (2005) positively link population density to metropolitan patenting, while Andersson, Quigley, and Wilhelmsson (2005) and Carlino, Chaterjee, and Hunt (2001, 2007) demonstrate the positive role of local employment density on innovation in Sweden and the United States, respectively. We construct a novel composite measure of population density, arguing that it better describes the geographic closeness of people than do previous conceptions of proximity and that it provides better intuition as to why the interactions between them occur.

Our approach also differs from previous density research by considering the effect of a specific form of density, namely the density of "creative capital."<sup>1</sup> Because innovation is an inherently creative act and not only traceable to those who meet a certain educational threshold, we feel that the concept of creative capital offers more precision than does the concept of education-based human capital measures. Highly creative and innovative people-such as Bill Gates-are included in the creative class, whereas they would be excluded from human capital measures. Additionally, as already discussed, we make use of population density measures instead of more commonly employed employment density measures because innovation and growth are not singularly institution- or firm-focused. Our central hypothesis is as follows: High densities of creative capital lead to frequent face-to-face interactions among individuals, thus facilitating "creative" spillovers and subsequent innovations.

In summary, innovation occurs when a person possessing creativity combines his or her existing expertise with observations learned through spillovers. Such spillovers occur when one individual's creativity is transferred to another individual or firm. These creative spillovers are in part believed to arise due to frequent face-to-face interactions and communication between individuals. Furthermore, these interactions are made more frequent by population density.<sup>2</sup> The literature also explains that geographical proximity (here conceived of as density) makes it more likely that the tacit (noncodified) knowledge essential to innovation and embodied in individuals will be shared through face-to-face contact<sup>3</sup> (Storper and Venables 2004). Gertler (2003, 79) explains that "tacit knowledge is a key determinant of the *geography* of innovative activity.... [B]ecause it defies easy articulation and is best acquired experientially, [it] is difficult to exchange over long distances."<sup>4</sup>

# Data and Methods

Our models examine the effects of density on innovation. We predict that metropolitan area density will increase the impact of creative capital on innovation, and that increasing returns to creative capital (creative spillovers) will be greater in the presence of high density. Empirically, this would mean that in an equation in which innovation is the dependent variable, interactions between density and creative capital would be positive, and that the effect size would be larger than an effect size for creative capital alone. A simple linear equation describes this hypothesis as follows.

Innovation =  $\beta_1 + \beta_2$ density +  $\beta_3$ creativity +  $\beta_4$ creativity\*density +  $\beta_5 R \& D$ +  $\beta_6$ Scientists & Engineers +  $\beta_7$ bohemians +  $\beta_8$  gays +  $\varepsilon$  (1)

As (1) suggests, many other variables have been linked to innovation either theoretically or empirically, and we therefore incorporate several of these into the analysis. First, much analysis, such as that of Griliches (1979), has been devoted to demonstrating the link between R&D expenditures and innovation. R&D should therefore be taken into account in any analysis that looks to explain innovation.

Second, studies by Florida and Gates (2001), Florida (2000, 2002a, 2002b), and Lee (2001) link the presence of both bohemians (defined as artists, musicians, writers, poets, etc.) and gays to innovation. This research suggests that bohemians are artistic innovators and that places that attract them have an environment that is open to new and different ideas. These same places are more likely to be open to technological innovators. Markoff's (2005) work on the history of technology in Silicon Valley elaborates this relationship, documenting not only the colocation of artistic and technological innovators, but also the social and spatial networks that connected them together and enabled them to influence one another. Thus, we also incorporate these variables into our analyses.

Our theory is that high densities of creatively oriented workers will promote metropolitan area innovation. Thus, we need measures of density, creativity, innovation, and other important controls (Table 1). The unit of analysis for this study is the Primary Metropolitan Statistical Area (PMSA), a geographical area that includes a central county and its economically related outlying territories. The U.S. Census periodically redefines the component units that comprise PMSAs and we use the 30 June 1999 definitions. We use PMSAs for several reasons. First, PMSAs capture economic spheres of influence. Second, given that this study hopes to identify relationships at a regional level, instead of at a smaller scale, the PMSA appears most appropriate. Note that all predictors chronologically precede the dependent variables included in the analysis.

## Density

We employ several variables of population density because no one measure fully captures the essence of the density construct. Instead, each measure reflects a different dimension. Each of the measures clearly has relative strengths and weaknesses, described in the following section. This definition is a fuller and more inclusive concept of density that is more reflective of the proximity of people discussed previously.

**Census Population Density.** The two simplest measures are 1990 Census population/1990 PMSA land area and 2000 Census population/1999 PMSA land area. We generated these measures by employing population data from the U.S. Census Bureau Web site (U.S. Census Bureau 2007a)<sup>5</sup> and land area data from the Census Factfinder site (U.S. Census Bureau 2007b). The population data are organized by Metropolitan Statistical Area (MSA) and all components, which include counties, towns, and so on. MSA land area<sup>6</sup> is found by locating the component land area (usually county) on the Factfinder site, and then aggregating these up to the MSA area. This is done for all MSAs and PMSAs. We divide MSA/PMSA population by the corresponding land area.

**Percentage Population in Urbanized Areas.** An alternative density measure is the percentage of MSA population in urbanized areas in 1990. Urbanized areas are defined by the U.S. Census Bureau to be areas with

Table 1. Descriptive statistics

Variable	No. Observations	Mean	SD	Min	Max
1990 Census population density	321	430.12	855.04	11.47	11768.06
2000 Census population density	331	438.08	921.36	5.41	12956.90
1982 urban density	325	2998.35	1764.19	647.32	22311.08
1997 urban density	327	2354.68	1261.82	775.32	12604.75
Percent in urbanized areas	326	69.45%	16.13%	21.50%	98.30%
Marginal density	325	997.86	1386.55	-4133.41	9318.94
Composite density	294	0.00	1.85	-2.09	18.62
1990 supercreative percent	273	8.91%	2.60%	4.35%	18.58%
1999 patents/100,000 pop.	331	25.39	31.89	0	281.06
1990 patents/100,000 pop.	313	17.47	16.95	0	111.10
1990 bohemian index	242	0.924	0.366	0.316	2.90
1990 scientists & engineers	273	0.719%	1.28%	0.02%	9.32%
1990 gay index	331	0.659	0.695	0.00	8.75
1990 state R&D/100,000 pop.	50	6334.29	2770.53	1950.11	20270.26
2000 Milken Tech-Pole	315	0.507	2.01	.000025	29.96
2000 Milken location quotient	346	0.827	0.726	0.032	5.167
2000 Milken tech share	346	9.23	28.53	0.0008	100
1990 citation weighted patents/100,000 pop.	309	121.83	144.59	0.764	890.10
1999 citation-weighted patents/100,000 pop.	329	1.043	2.06	0.00	19.08
1999 industry-weighted patents/100,000 pop.	329	22.24	21.70	0.151	156.61

*Note*: R&D = research and development.

a population density of at least 1,000 people per square mile. This measure also makes use of 1990 census data. Henceforth, this measure is called percent in UA.

Urban Density. Fulton et al. (2001) compute density measures for 1982 and 1997, but instead of using just land area in the denominator, they derive acres devoted to urban uses from the National Resources Institute's (NRI) national survey of land use. We convert acres to square miles. This measure, PMSA population divided by urban square miles, is calculated for both 1982 and 1997. Because we know the change in population for 1982 to 1997 and the change in urbanized square miles for 1982 to 1997, we can divide the two, and thus calculate the marginal density to find out how many people were added to the PMSA over the fifteenyear span for each new square mile of land developed for urban use. The authors note that their measures are not simply residential densities, but overall densities based on all land urbanized to meet population growth.<sup>7</sup>

Each density measure has strengths and weaknesses and therefore is included in the analysis for different reasons. A major strength of the Census population density measure is that it is conceptually simple; it provides a simple average density for each MSA and is easy to interpret. Furthermore, given that it measures residential population density, it gives an intuitive description of the closeness of people to one another in an MSA and is reflective of our theory. Last, the data to construct these measures are readily available, even down to small units such as tracts. Yet, Census density has several weaknesses. First, given that the total land area for an MSA or PMSA changes very little across years, over time, the variables primarily reflect population changes, even accounting for changes to MSA definitions. These measures also abstract out a large amount of information. Specifically, they do not depict how population is distributed within an MSA, instead, often incorrectly, averaging population evenly over the entire MSA.

The urban density measures, along with marginal density, have distinctive strengths. The Fulton et al. (2001) study was the first to measure metropolitan area density using an actual measurement of urban land. Given that urbanized land has been drastically increasing over time, we are more likely to observe decreases in density over time than with the Census population density measures if population grows at a slower rate. Clearly, these measures more closely track increases in urban lands and show how density reacts to these changes over time. Thus, these measures are not simply charting changes in population, but instead are documenting relationships between population and land area, and doing a better job at this than Census population density.<sup>8</sup> Yet, similar to Census population density, these measures also are only an average density across the entire MSA or PMSA, and thus abstract out much information about how population is distributed within an MSA or PMSA.

To the extent that the percent in UA measure defines land as urban by its ability to meet a particular residential density threshold, it once again captures the notion of the closeness of people depicted in the theory section. This measure is not explicitly density, but instead only a description of a minimum density. With this measure we do not even have an estimate of an average density across the whole MSA and do not know whether most of an MSA contains densities close to the threshold, or whether segments of an MSA have densities high above it. Here, too, much information is abstracted away.

Instead of measuring employment density, as do Carlino, Chaterjee, and Hunt (2001, 2007), we use measures of population density. This choice stems from theory. We prefer not to restrict the interactions to ones occurring at work or in employment environments. Urban, dense places make possible many kinds of interactions, in different places and among and between many kinds of people. We posit that these diverse interactions promote innovations and that there is benefit to keeping the definition of density broad.

## Methods

**Principal Components Analysis.** Given the similarities among these density measures, substantial multicollinearity might exist between them, thus complicating attempts to attribute explanatory power in a regression to any or all of these variables. Indeed, Pearson and Spearman correlations among these variables

reveal such multicollinearity (see Table 2). To avoid multicollinearity between the density variables and also allow for more parsimonious models and improved measurement of indirectly observed concepts (Hamilton 1992), we employ principal components analysis to construct one composite density measure. The component explaining the majority of the variance in the six density variables also has positive loadings on all six measures, and thus can be interpreted as a density component (see Table 3). We create a composite density index by linearly combining the six density variables, standardized and weighted by the component loadings.<sup>9</sup>

Table 4 illustrates several MSAs measured on each of the density measures, including the composite index. Given that the composite index is a linear combination of standardized variables, positive observations indicate above-average densities, whereas negative values indicate below-average densities.

**Innovation.** The dependent variable is 1999 metropolitan area utility patents per 100,000 people. As explained by the U.S. Patent and Trademark Office, "utility patents may be granted to anyone who invents or discovers any new and useful process, machine, article of manufacture, or composition of matter, or any new and useful improvement thereof" (U.S. Patent and Trademark Office 2007). We measure innovation by using simple utility patent count data downloaded from Hall, Jaffe, and Trajtenberg's (2001) National Bureau of Economic Research patent database, but originally available from the U.S. Patent and Trademark Office. Also, as described later, we use 1990 metropolitan area utility patents per 100,000 people as an independent variable. Hall, Jaffe, and Trajtenberg note that patents

Table 2. Density correlation matrices

	(1)	(2)	(3)	(4)	(5)	(6)
	(1)	(2)	(3)	(1)	())	(0)
Pearson correlations						
(1) Census density 1990	1.0000					
(2) Census density 2000	0.9948	1.0000				
(3) Percent in urbanized area	0.3068	0.3001	1.0000			
(4) Urban density 1982	0.5375	0.5298	0.2556	1.0000		
(5) Urban density 1997	0.7557	0.751	0.3751	0.7298	1.0000	
(6) Marginal density	0.0447	0.0622	0.3008	0.1959	0.4565	1.0000
Spearman correlations						
(1) Census density 1990	1.0000					
(2) Census density 2000	0.9645	1.0000				
(3) Percent in urbanized area	0.4405	0.4403	1.0000			
(4) Urban density 1982	0.3504	0.3159	0.3023	1.0000		
(5) Urban density 1997	0.3943	0.3786	0.4285	0.8712	1.0000	
(6) Marginal density	0.1523	0.1940	0.3173	0.1005	0.3606	1.0000
-						

Component	Eigeı	nvalue	Differ	ence	Proportion	l	Cumulative
1	3.4	1978	978 2.21252		0.5700		0.5700
2	1.2	0726	0.47	018	0.2012		0.7712
3	0.7	3708	0.21	0.21352		0.1228	
4	0.5	2356	0.41	564	0.1228		0.9813
5	0.1	0792	0.10	352	0.0180		0.9993
6	0.0	0440	_	-	0.0007		1.0000
				Compone	ents loadings		
Variable		1	2	3	4	5	6
1990 Census density		0.48519	-0.32814	0.12749	-0.29376	0.22722	0.70903
2000 Census density		0.48757	-0.31512	0.11395	-0.30581	0.24409	-0.70490
1982 Urban density		0.40929	-0.01205	-0.38352	0.76710	0.31113	0.00142
1997 Urban density		0.50456	0.11863	-0.22743	-0.04724	-0.82302	-0.00530
Percent in urbanized ar	ea	0.26572	0.43773	0.81279	0.27735	-0.01449	-0.00584
Marginal density		0.18482	0.76629	-0.33366	-0.39061	0.33826	0.0179
			Scoring coef	ficients			
		Variable	2		1		
		1990 Ce	ensus density	C	.48519		
		2000 Census density		C	.48757		
		1982 Ui	ban density	C	0.40929		
		1997 Ui	ban density	C	).50456		
		Percent	in urbanized	area (	0.26572		
		Margina	al density	C	0.18482		

Table 3. Principal components analysis

Principal components; six components retained.

have numerous advantages as data for the study of innovation and technological change. Patents contain highly detailed information on the innovation itself, but also about the inventor, the originating technological area(s) and industry, and so on. In addition, there is both a very large "stock" and "flow" of patents, so there exists a wealth of data available for research. Griliches (1990) and Scherer (1983) both note the extent to which there exists a strong relationship between industrial patenting and the conduct of R&D, implying that patents are a good measure of inventive activity. Patent count data reach back at least one hundred years, making available long time series of data. Several recent papers point to patents as appropriate measures of spatial innovativeness and geographical information. Ó hUallacháin and Leslie (2005) and Ceh (2001) use patent counts as a measure of the innovative potential of U.S. states, finding over the past several decades a marked shift in inventive activity from the traditional manufacturing belt to the western states. Ó hUallacháin (1999) probes the geography of innovation by exploring metropolitan areas and patents, and finds that most patents awarded to Americans are obtained by residents of metropolitan areas, with large metros predominating. Of course, simple patent count data also have serious limitations. First, as Griliches (1990) points out, not all inventions or innovative ideas are patented or patentable. Second, as Hall, Jaffe, and Traitenberg (2001) and Griliches (1990) recognize, innovations differ enormously in their technological and economic importance and patent counts are seriously insufficient in their ability to capture this underlying heterogeneity. Instead, as Trajtenberg (1990) notes, patent counts are found to be indicative of the input side of the innovative process, as in R&D expenditures. To address these limitations, our analyses are also conducted using citation-weighted patents as the dependent variable, as "patent counts weighted by a citations-based index appear to be highly correlated (over time) with independent measures of the social gains from innovations" (Traitenberg 1990, 172). Additionally, the shift to a knowledge-based, serviceoriented economy from manufacturing creates important shortcomings with patent data. Specifically, Hipp and Grupp (2005, 524-25) suggest that because the service innovation process "does not necessarily aim to acquire or generate technical know-how," patents play

$\begin{array}{c c c c c c c c c c c c c c c c c c c $	Region	Census population density <sup>a</sup>	Urban density <sup>b</sup>	Marginal density	Percent in urbanized area	Composite index
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	>1,000,000 persons					
756.243208.2Pittsburgh, PA584.73441.3 $-581.9$ 71% $-0.01$ Boston, MA1632.84161.6646.177%1.861694.52956.611694.52956.61New York City7490.713560.24090.892%14.84 $>500,000$ and <1,000,000 persons	Washington, DC	989.55	3990.9	1890.9	78%	1.26
Pittsburgh, PA584.7 $3441.3$ $510.0$ $-581.9$ $2239.4$ $71\%$ $-0.01Boston, MA1632.84161.6646.177\%1.86New York City7490.713560.24090.892\%14.848163.212438.624090.892\%14.84> 500,000 and <1,000,000 persons$		756.24	3208.2			
$\begin{array}{c ccccc} 510.0 & 2239.4 \\ \hline Boston, MA & 1632.8 & 4161.6 & 646.1 & 77\% & 1.86 \\ 1694.5 & 2956.6 & 2970.3 & 308.78 & 82\% & 0.37 \\ \hline & 8163.2 & 12438.6 & & & & & \\ \hline & 8163.2 & 12438.6 & & & & \\ \hline & 8163.2 & 12438.6 & & & & \\ \hline & & & & & & \\ \hline & & & & & &$	Pittsburgh, PA	584.7	3441.3	-581.9	71%	-0.01
Boston, MA1632.84161.6646.1 $77\%$ 1.86New York City7490.713560.24090.892%14.848163.212438.612438.612438.6>500,000 and <1,000,000 persons		510.0	2239.4			
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Boston, MA	1632.8	4161.6	646.1	77%	1.86
New York City7490.7 8163.213560.2 12438.64090.8 92%92% 14.84 8163.2> 500,000 and <1,000,000 persons		1694.5	2956.6			
$ \begin{array}{c c c c c c c c c c c c c c c c c c c $	New York City	7490.7	13560.2	4090.8	92%	14.84
		8163.2	12438.6			
Akron, OH726.62970.3308.7883%0.37 $767.9$ 2135.62135.612956.912604.818.62Little Rock, AR176.52087.5784.854%-1.01 $200.8$ 1719.7200.81719.71160.21764.6Tulsa, OK141.42103.6650.366%-0.84 $160.2$ 1764.6764.6764.6765.9 $>250,000$ and <500,000 persons	>500,000 and <1,000,000 persons					
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Akron, OH	726.6	2970.3	308.78	83%	0.37
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		767.9	2135.6			
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Jersey City, NJ	11768.1	13611.6	-4133.4	92%	18.62
Little Rock, AR176.52087.5784.854% $-1.01$ 200.81719.7Tulsa, OK141.42103.6650.366% $-0.84$ 160.21764.6> 250,000 and <500,000 persons		12956.9	12604.8			
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Little Rock, AR	176.5	2087.5	784.8	54%	-1.01
Tulsa, OK141.4 160.22103.6 1764.6650.3 66% $-0.84$ -0.84>250,000 and <500,000 persons Columbus, GA219.8 174.9 $3137.9$ 1889.5 $232.3$ 83% $-0.28$ -0.45Corpus Christi, TX228.9 249.22417.1 1923.4 $722.7$ 76% $-0.45$ -0.45Lancaster, PA445.5 496.02354.6 1973.61144.4 760 $45\%$ -0.66 496.0 $-0.66$ 496.0Trenton, NJ1441.7 152.03499.3 2699.3616.1 616.1 $92\%$ 90% $-0.69$ -0.09  Abilene, TX130.6 138.2 130.6 $3124.3$ 2301.9 $111.9$ 90% $-0.09$ -0.09Bellingham, WA $60.3$ 78.7 2044.2 $2121.7$ 1874.9 $1874.9$ 44% $-1.02$ 78.7 2044.2Duluth-Superior, MN-WI $31.9$ 2097.3 29.3 1494.4 $521.4$ 75% $75\%$ -1.22 31.9 $-1.22$ 31.9		200.8	1719.7			
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	Tulsa, OK	141.4	2103.6	650.3	66%	-0.84
$\begin{array}{c c c c c c c c c c c c c c c c c c c $		160.2	1764.6			
$\begin{array}{c c} \mbox{Columbus, GA} & 219.8 & 3137.9 & 232.3 & 83\% & -0.28 \\ 174.9 & 1889.5 & & & & & & & & \\ \mbox{Corpus Christi, TX} & 228.9 & 2417.1 & 722.7 & 76\% & -0.45 \\ 249.2 & 1923.4 & & & & & \\ \mbox{Lancaster, PA} & 445.5 & 2354.6 & 1144.4 & 45\% & -0.66 \\ 496.0 & 1973.6 & & & & & \\ \mbox{Trenton, NJ} & 1441.7 & 3499.3 & 616.1 & 92\% & 1.66 \\ 1552.0 & 2699.3 & & & & \\ \mbox{Columbus, GA} & & & & & & \\ \mbox{250,000 persons} & & & & & & \\ \mbox{Abilene, TX} & 130.6 & 3124.3 & 111.9 & 90\% & -0.09 \\ \mbox{138.2 & 2301.9 } & & & & \\ \mbox{Bellingham, WA} & 60.3 & 2121.7 & 1874.9 & 44\% & -1.02 \\ \mbox{78.7 & 2044.2 } & & & & \\ \mbox{Duluth-Superior, MN-WI} & 31.9 & 2097.3 & -639.6 & 51\% & -1.51 \\ \mbox{32.4 & 1454.9 } & & & \\ \mbox{Rapid City, SD} & 29.3 & 1494.4 & 521.4 & 75\% & -1.22 \\ \mbox{31.9 & 1134.5 } & & & & \\ \end{tabular}$	>250,000 and <500,000 persons					
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Columbus, GA	219.8	3137.9	232.3	83%	-0.28
Corpus Christi, TX       228.9       2417.1       722.7       76%       -0.45         Lancaster, PA       445.5       2354.6       1144.4       45%       -0.66         496.0       1973.6       192.3       100       100       100         Trenton, NJ       1441.7       3499.3       616.1       92%       1.66         250,000 persons       1552.0       2699.3       -0.09       138.2       2301.9       -0.09         Bellingham, WA       60.3       2121.7       1874.9       44%       -1.02         78.7       2044.2       -1.51       32.4       1454.9       -1.51         Rapid City, SD       29.3       1494.4       521.4       75%       -1.22         31.9       1134.5       1134.5       -1.22       -1.22		174.9	1889.5			
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Corpus Christi, TX	228.9	2417.1	722.7	76%	-0.45
Lancaster, PA 445.5 2354.6 1144.4 45% -0.66 496.0 1973.6 Trenton, NJ 1441.7 3499.3 616.1 92% 1.66 1552.0 2699.3 <250,000 persons Abilene, TX 130.6 3124.3 111.9 90% -0.09 138.2 2301.9 Bellingham, WA 60.3 2121.7 1874.9 44% -1.02 78.7 2044.2 Duluth-Superior, MN-WI 31.9 2097.3 -639.6 51% -1.51 32.4 1454.9 Rapid City, SD 29.3 1494.4 521.4 75% -1.22 31.9 1134.5		249.2	1923.4			
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Lancaster, PA	445.5	2354.6	1144.4	45%	-0.66
Trenton, NJ       1441.7       3499.3       616.1       92%       1.66         <250,000 persons		496.0	1973.6			
1552.0       2699.3         <250,000 persons	Trenton, NJ	1441.7	3499.3	616.1	92%	1.66
<250,000 persons Abilene, TX 130.6 3124.3 111.9 90% -0.09 138.2 2301.9 Bellingham, WA 60.3 2121.7 1874.9 44% -1.02 78.7 2044.2 Duluth-Superior, MN-WI 31.9 2097.3 -639.6 51% -1.51 32.4 1454.9 Rapid City, SD 29.3 1494.4 521.4 75% -1.22 31.9 1134.5		1552.0	2699.3			
Abilene, TX       130.6       3124.3       111.9       90%       -0.09         138.2       2301.9       2301.9       -0.09         Bellingham, WA       60.3       2121.7       1874.9       44%       -1.02         Duluth-Superior, MN-WI       31.9       2097.3       -639.6       51%       -1.51         32.4       1454.9       1494.4       521.4       75%       -1.22         31.9       1134.5       1134.5       -1.22       -1.22	<250,000 persons					
Bellingham, WA       138.2       2301.9         Bellingham, WA       60.3       2121.7       1874.9       44%       -1.02         78.7       2044.2       78.7       2097.3       -639.6       51%       -1.51         32.4       1454.9       1454.9       75%       -1.22         Rapid City, SD       29.3       1494.4       521.4       75%       -1.22         31.9       1134.5       1134.5       75%       -1.22	Abilene, TX	130.6	3124.3	111.9	90%	-0.09
Bellingham, WA       60.3       2121.7       1874.9       44%       -1.02         78.7       2044.2       78.7       2044.2       -1.51         Duluth-Superior, MN-WI       31.9       2097.3       -639.6       51%       -1.51         32.4       1454.9       1454.9       -1.22       -1.22       31.9       1134.5		138.2	2301.9			
78.7       2044.2         Duluth-Superior, MN-WI       31.9       2097.3       -639.6       51%       -1.51         32.4       1454.9         Rapid City, SD       29.3       1494.4       521.4       75%       -1.22         31.9       1134.5	Bellingham, WA	60.3	2121.7	1874.9	44%	-1.02
Duluth-Superior, MN-WI         31.9         2097.3         -639.6         51%         -1.51           32.4         1454.9         -         1.51         -         -         -         1.51         -         -         1.51         -         -         1.51         -         1.51         -         1.51         -         1.51         -         1.51         -         1.51         -         1.51         -         1.51         -         1.51         -         1.51         -         1.51         -         1.51         -         1.51         -         1.51         -         1.51         -         1.51         -         1.51         -         1.51         1.51         -         1.51         1.51         -         1.51         1.51         <		78.7	2044.2			
32.4       1454.9         Rapid City, SD       29.3       1494.4       521.4       75%       -1.22         31.9       1134.5	Duluth-Superior, MN-WI	31.9	2097.3	-639.6	51%	-1.51
Rapid City, SD29.31494.4521.475%-1.2231.91134.5		32.4	1454.9			
31.9 1134.5	Rapid City, SD	29.3	1494.4	521.4	75%	-1.22
		31.9	1134.5			

 Table 4. Density measures

<sup>*a*</sup>Top value refers to 1990 and bottom value refers to 2000.

<sup>b</sup>Top value refers to 1982 and bottom value refers to 1997.

a limited role. A final shortcoming of simple patent counts is that patents are heavily concentrated in specific industries. For example, patents work especially well in biotechnology, an industry heavily tied to universities. Because our patent data reveal the industry to which the patent applies, we can also construct industry-weighted patent data, and we also conduct all analyses with this dependent variable.

**Creative Capital.** This is a measure invented by Florida and Stolarick (introduced in Florida 2002c) using data from the 1999 Bureau of Labor Statistics Oc-

cupational Employment Statistics Survey. The measure is used to capture all employment in a region that has a creative component. The survey provides counts of employees in different occupational categories, so we can compute the percentage of creative employees for each PMSA. Yet, because the explanatory variables must temporally precede the dependent variables to simulate causation, and because the Florida–Stolarick measure uses data from the same year as the innovation data, we had to re-create the creative capital variable using the 1990 Decennial 5 percent Census Public Use Microdata Sample (PUMS).<sup>10</sup> As mentioned, studies by Florida and Gates (2001), Florida (2000, 2002a, 2002b), Lee (2001), and Lee, Florida, and Acs (2004) link the presence of gays and bohemians to innovation, growth, or new firm formation. They explain this linkage by claiming that new ideas arise due to a multiplicity of people and perspectives, and that the presence of gays and bohemians in metropolitan areas is indicative of a tolerance of a wide variety of people. Thus, we want to account and control for these factors in our regressions.

**Gay Index.** This variable, originally calculated by Black et al. (2000), is based on the 1990 PUMS data, as a location quotient measuring the over- or underrepresentation of coupled gays and lesbians in an MSA. See Black et al. (2000) for more information on this measure.

**Bohemian Index.** This variable, attributable to Florida (2000, 2002a, 2002b), is also based on the 1990 PUMS and is a location quotient of the number of bohemians in an MSA. As Lee, Florida, and Acs (2004) note, it includes authors, designers, musicians, composers, actors, directors, painters, sculptors, craft-artists, artist printmakers, photographers, dancers, artists, and performers.

**Research and Development.** MSA-level total R&D is not available and must be estimated. A simple estimate is a linear combination of state-level R&D and the MSA-level percentage of scientists and engineers. We employ a very unrestrictive combination, by simply additively including the two variables in a linear regression. State-level R&D is available via the National Science Foundation's WebCASPAR (2007). As noted by Lee (2001), scientists and engineers serve as a proxy for R&D expenditures. Data on scientists and engineers as a percentage of total MSA employment are available from the 1990 Decennial 5 percent Census PUMS, calculated on a per-capita basis.

**Milken Tech-Pole Index.** As DeVol et al. (2001, 38) state, "Regional clusters [of high-tech industry] may be more important in fostering innovative economic activity than the large multinational corporations that engage in promoting it." Potentially, the prevalence or spatial concentration of high-tech industry in a metropolitan area could be highly related to the metro's capacity for innovation. Thus, measures of this concentration are used here as proxies for patents to test the

robustness of the empirical models. We make use of the measures of high-technology industry spatial concentration constructed by DeVol et al. of the Milken Institute. They form their Tech-Pole index by multiplying together their two individual measures of concentration, (1) high-tech location quotient<sup>11</sup> and (2) the metro area proportion of national high-tech output. The location quotient effectively measures the importance of an industry to a local economy, but unfortunately does not adjust for the size of the city. Therefore, on this measure, the impact of small metros with high local concentrations of high-tech industry on the national economy might be exaggerated. Likewise, large metros might rank highly on the measure of metro area proportion of national high-tech output simply due to their size. To alleviate these concerns, DeVol et al. formed a composite index that combines the two measures by multiplying them. The composite measure is their Tech-Pole, which is intended to measure the technological "gravitational pull" that a metro exerts.

Creative–Density Interaction. To assess the joint effects of creativity and density on innovation, we construct a multiplicative interaction term of the scaled composite density index and percentage creative capital. We feel this measure provides a good proxy for the actual density of creative capital.<sup>12</sup> One would expect actual creative density to increase with overall density and, fortunately, we observe our interaction term increasing with overall density. This variable is of primary interest in our empirical tests, and if our theories are borne out by the data, we expect this interaction term to obtain a positive coefficient. A final comment about this measure should be made. Clearly, creative capital is comprised of engineers, scientists, artists, architects, athletes, and several other occupations. Obviously, this measure is present in all regressions but, importantly, also included separately are bohemians and percent scientists and engineers. Seemingly, one could raise the objection that we double-count scientists and engineers and bohemians, given that they are controls in the regressions and are part of the creativity measure. We feel, however, that creative capital should be conceived as an entity unto itself, and that important reactions or interplay occur when its individual components are interspersed together. So, the whole is greater than the sum of its parts. We still need to account in a regression for the individual effects of scientists and engineers and bohemians, to reinforce the predominant importance of the reactions described earlier.

## Findings

## **Regression Estimation Results**

We estimated a series of regressions and other tests to assess the evidence for our theories.<sup>13</sup> Table 5 provides ordinary least squares estimation results using 1999 patents per 100,000 people as the dependent variable. The results provide ample evidence in support of our theory. The coefficient on the creativity-density interaction term from this regression is positive (2792.2) and significant, as expected. This result lends weight to our hypothesis that the density of creative workers facilitates innovation. Furthermore, we might be interested in the marginal effects of the composite density index and 1990 percent supercreative employment on 1999 patents per 100,000 people. To recover these marginal effects, we compute the respective coefficients with all other variables at their means. When this is done, we observe that the composite density index coefficient is now positive (30.96), and the creative capital coefficient is also positive (222.9). These results both align with our theories.

An unexpected result is that the percentage of scientists and engineers appears to have a negative impact on 1999 patents per 100,000. Several explanations are available. As Chapple et al. (2004) point out, metropolitan areas with high employment shares in high-tech occupations are often smaller, emergent regions such as Austin or Raleigh-Durham. Such places might not be sufficiently diversified occupationally to engender high rates of inventive activity. Chapple et al. conclude that high-tech employment share measures might thus penalize larger cities with a large number of high-tech occupations but a more diversified economy. Additionally, different industries have different propensities to patent. Such differences are lost in an overall share measure of the sort employed here. Finally, we might conjecture that the negative correlation is actually a reflection of scientific or research bureaucracy. More scientists and engineers might entail (1) more

Dependent variable:					
1999 patents/100,000 population	(1)	(2)	(3)	(4)	(5)
Independent variables					
Composite density index <sup>a</sup>	-306.89	-218.10	2.32	-323.80	-3.47
	(0.000)	(0.000)	(0.899)	(0.000)	(0.850)
1990 % supercreative employment <sup>a</sup>	152.72	-59.20	180.99	66.03	
	(0.183)	(.534)	(0.012)	(0.593)	
Creativity-density interaction term	4032.35	2792.2		4082.7	
	(0.000)	(0.000)		(0.000)	
1990 bohemian index		-0.100	-1.16	12.60	4.65
		(0.986)	(0.847)	(0.096)	(0.409)
1990 percent scientist & engineers		-162.41	33.33	-97.51	42.44
		(0.252)	(0.805)	(0.598)	(0.756)
1990 gay index		4.00	5.19	1.63	5.49
		(0.116)	(0.046)	(0.622)	(0.037)
1990 state R&D/100,000 population		-0.00025	-0.00005	-0.00077	0.00019
		(.701)	(0.939)	(0.359)	(0.764)
1990 patents/100,000 population		1.27	1.32		1.39
		(0.000)	(0.000)		(0.000)
Constant	6.41	5.616	-15.53	8.26	-7.09
	(0.520)	(.520)	(0.024)	(0.468)	(0.238)
Adjusted R <sup>2</sup>	0.2614	0.5694	0.5454	0.2669	0.535
Ν	240	240	240	240	240

Table 5. Ordinary least squares regression with patents

*Note: p* value in parentheses. R&D = research and development.

<sup>*a*</sup> To recover the marginal effects of both the composite density index and 1990 percent supercreative employment, we compute the respective coefficients with all other variables at their means (from the second column). When this is done, we observe:

1. (1999 patents/100,000 population) = 22.3 + 30.96 (composite density index)

2. (1999 patents/100,000 population) = 5.6 + 222.9 (1990 percent supercreative employment)

Clearly, the coefficients on density and creativity are both positive, as theory would predict.

overhead and not necessarily better innovative results, or (2) patents registered elsewhere by a multilocational firm.

Also notable from Table 5 is the insignificance of both the bohemian and gay indexes. Apparently, relative to the effects of creative density, these variables, along with percentage of scientists and engineers, play a lesser role in facilitating innovation. The noticeable positive effects of the creative-density term on innovation as compared to the negligible effects of bohemians and scientists and engineers taken alone point to the importance of conceiving of a more inclusive creative class, as Florida (2002c) does. For the current analysis, however, it especially points to the importance of the interactions between the members of this broader class. As postulated earlier, the whole of this class is greater than the sum of its parts, in large part due to the relationships among its members that are made possible by density.<sup>14</sup> Finally, we note the very small, insignificant coefficient on 1990 state total R&D per 100,000 people. First, given that this variable is measured at the state level instead of at the PMSA level, potentially it does not achieve as much variation as our other variables, thus affecting its usefulness in hypothesis testing. Theoretically, however, the slightly negative coefficient could indicate that there are decreasing returns to R&D dollars, which is a fairly standard conclusion in contemporary R&D research.

Regressions Estimations by Metro Size. Although all of the variables included in regressions to this point have been in per-capita terms, we have not sufficiently dealt with the possibility that creative density might have a different effect on innovation among cities of different sizes.<sup>15</sup> In other words, we need to consider the possibility that size and density might interact. For example, we might think that even after variables are in per-capita terms, bigger cities have inherent qualities or advantages that increase the effect of creative density on innovation. Of course, there is also the issue that bigger cities are typically denser, which is demonstrated by the correlation of 0.53 between the composite density measure and 2000 population. To account for this potential interaction, we first estimated four separate regressions for various metro size quartiles (1 million and above, 500,000–1 million, 250,000–500,000, and less than 250,000). The overriding result suggests that, in fact, the effect of creative density on innovation is in absolute terms largest for the largest metros (above 1 million population), and the relationship is

Table 6.	Ordinary I	east square	s regression	with pat	ents,
	contr	olling for p	opulation		

Dependent variable: 1999 Patents/		
100,000 population	(1)	(2)
Independent variables		
Composite density index	-440.08	-296.51
	(0.000)	(0.000)
1990 % Supercreative employment	-87.37	-216.23
	(0.475)	(0.037)
Creativity–Density interaction term	6636.42	4344.53
	(0.000)	(0.000)
(Creativity–Density) $\times$ 1990 population	-0.0002	-0.0002
	(0.000)	(0.001)
1990 bohemian index		5.38
		(0.366)
1990 percent scientist & engineers		1.19
		(0.993)
1990 gay index		1.63
		(0.527)
1990 state R&D/100,000 population		-0.0004
		(0.534)
1990 patents/100,000 population		1.18
		(0.000)
Constant	19.81	12.81
	(0.049)	(0.145)
Adjusted <i>R</i> <sup>2</sup>	0.3177	0.5892
N	240	240

*Note: p* value in parentheses. R&D = research and development.

only significant at that size level. These results reflect those of Ó hUallacháin (1999, 614), who found that the largest U.S. metropolitan areas garner the majority of patents awarded to Americans. O hUallacháin proposed that the innovative advantages accruing to big cities arose from "lopsided concentrations of technologically intensive manufacturing sectors and an uneven distribution of well-educated people." This result does not imply that creative density does not matter and that metro size is the only meaningful explanatory factor, but that creative density and size positively interact. Of course, these quartiles are somewhat arbitrary, so another option is to estimate one regression with a creative density \* population interaction term. When we estimate this regression (see Table 6) with 1999 patents per 100,000, the coefficient on creative density is again positive and significant, and in fact has a larger coefficient than in Table 5 (4344.5 to 2792.2). Interestingly, the effect of the interaction between creative density and population on patents is close to zero and significant. Seemingly then, these city size results are mixed.16

#### **Causality Issues**

We briefly discuss our methods for dealing with potential reverse causality or endogeneity questions in our models. To mitigate the possibility that causality might run in the opposite direction, we ensure the appropriate temporal nature of our variables, making sure all of the independent variables precede the dependent variables. Second, we control for the initial stock of innovation, thus separating the role of creativity and density from their capacity for just proxying for innovation.

More specifically, one might argue that innovation raises incomes, thus raising people's abilities and desires to fund museums and other artistic undertakings. We recognize this as a potential issue, and could look for instruments for our creativity measures. One such measure might be per-capita spending on the arts, or the incidence of artistic occupations within a metropolitan area (Markusen and King 2003); however, the creative measure is a broader metric, capturing artists, computer scientists, scientists, architects, and education workers. These proposed instruments would only reflect "bohemian" culture, yet the creative measure is not a proxy for bohemians. Importantly, we find that bohemians do not significantly enter regressions when they are included alongside creatives, evidence against the art funding and artistic occupations arguments.

## **Future Research**

Although outside the scope of this research project, several interesting possibilities remain for future research. As mentioned, we would like to evaluate the effect of the absolute number of creative workers on innovation and also create an actual creative density measure. Potentially more pressing is the fact that our density measures neglect differences in density within metro areas, instead averaging over these differences. To deal with this problem, we could create a weighted average density measure, weighting by the population of each census tract, and then aggregating up to the MSA.<sup>17</sup> Clearly then, dense, highly populated tracts would be weighted heavily.

As the data become available, it would also be preferable to consider analyses done in this study at a unit smaller than the MSA/PMSA (Lang and Danielsen 2005, 207; Sawicki 2003, 91). For the purposes of deciphering how population density relates to and influences idea flows and knowledge generation, the metropolitan area is likely too large a unit of observation. This is especially true if the majority of "new knowledge" flows from particular clusters in the MSA or PMSA, like a central city or county. If we were to use a smaller unit of observation, when we computed the measure of patents per capita, we would no longer divide the number of patents by the total MSA population as we do now, but only by the clusters' population. Thus, not only would we observe higher patents per capita, but likely also a greater association between new knowledge and density. This caveat aside, for a first take, observing these relationships at the MSA or PMSA level is still a useful exercise.

Lang and Danielsen (2005, 206) argue that Florida does not sufficiently justify how and why geography and place matter in making the creative class. They wonder why Florida did not address "how creative subcultures form, how [they] are sustained, . . . and [whether] there are intrinsic qualities to certain cities in terms of their 'urban' quality that would predict the rise of creative subcultures?" Lang and Danielsen refer to Claude Fischer's important suggestion that higher urban density leads to more intense and varied subcultures. Future research would more fully investigate this important relationship among density, size, and urban creative subcultures. Milligan (2003, 24) suggests that there "is a strong argument to be made for the role of the built environment in stimulating tolerance, creating awareness of social problems, and promoting certain forms of interaction." Future research might look into how variations in urban form and design affect the presence of the creative class in cities as well as innovative activity.

Future study could also more fully explore issues surrounding the geography of patenting activity. For instance, future analysis could detail the relationships among the addresses of patentees, the addresses of associated corporations, law firms, and offices used for registering the patents. In addition, future research could also look into the relationships between patents granted to companies located inside the United States, but with foreign head offices. Such research would address issues of "multiple scales" raised by Bunnell and Coe (2001).

Whereas our work used cross-sectional data to examine the links among density, creativity, and innovation, it remains for case or ethnographic studies to elaborate more fully the conditions on the ground. Such case work could add detail to considerations of spillovers, face-to-face interactions, density, and innovation, also enabling treatment of factors such as ethnicity, gender, age, and class.

Finally, a future historical analysis might lag density to the age of the city to take into account the state of transport costs at the time of urbanization. One might argue that old places like New York are dense because transport costs were higher as the city was urbanizing, as compared to Los Angeles.

# Conclusions

Our research has examined the role of density and creativity in metropolitan area innovation. Using linear regression, we examined the joint and separate effects of population density and creativity on innovation for 240 metropolitan areas in the United States. We employed principal components analysis to construct a novel composite population density measure, which was then intersected with a creative occupations measure to give our final creative density variable. These analyses tested our major hypothesis that high densities of creative individuals would promote more frequent faceto-face interactions, thus facilitating creative spillovers, and subsequently innovations.

Our finding that creative density enters positively and significantly in a regression with patents as the dependent variable supports our hypothesis that the density of creative workers promotes innovation. Additionally, we found that the marginal effects for density and creativity, taken separately, both exhibit positive relationships with metropolitan patenting. These results strongly reinforce the extant geographic literature on spillovers and agglomeration, which posits that innovation, learning, and knowledge creation are strongly geographically and spatially mediated. Strong currents in geography and social science hold that proximity matters, and this research is firmly situated in that tradition. Also, these results support recent claims that intellectual human capital embodied in individuals is also predictive of and important for innovation. However, our research and findings extend these two previous traditions in several crucial ways. First, they merge them by asserting that proximity and intellectual human capital work together to power innovation. It is the geographic concentration of people with expertise, skills, and knowledge that powers the exchange and spillovers that precede innovation. Our analysis, especially the construction of our creative density measure, reflects this important observation. Second, we propose population density as a specific conception of geographic proximity that better explains and accounts for the actual face-to-face interactions that underlie knowledge spillovers. We consider this an important improvement over past geographical studies on innovation. Third, we employ an occupation-based measure

of intellectual human capital—creative occupations building on and extending Florida's important contributions in this area. Taken together, our approach and findings point to a new direction for geographic research, and consequently, we hope that this study encourages a fuller understanding of the spatial determinants of innovation.

# Acknowledgments

We would like to thank two anonymous reviewers for their comments, and the *Annals* editor for her careful attention. Elizabeth Currid also read and commented on an earlier draft.

## Notes

- 1. Florida's creativity theory attempts to specify precise linkages and mechanisms between tolerance and talent, between talent and innovation, and between innovation and growth. Florida (2002b) shows these linkages with a path model that specifies the links among tolerance, talent, innovation, and income growth. These linkages are also guite clearly spelled out and developed in Florida (2005). In contrast to extant theory, Florida's creativity theory says that talent is not a stock with which regions are endowed, but a flow that depends on tolerance or openness. Accordingly, places that are open to artistic innovators will be more likely to produce, retain, and attract innovators of all sorts, including technological innovators. Places that produce, attract, and retain more technological innovators and combine them with Schumpeterian economic innovators or entrepreneurs will be more likely to generate new firms and industries and thus to grow. This article does not attempt to test the entirety of this relationship but focuses in detail on one key component—one central mechanism—and that is the effect of geographic concentration or density on this process. It goes beyond the extant literature on the question by specifying the role of this quintessentially spatial element, density, as a key element of the black box of innovation.
- 2. Density is what enables frequent, unpredictable, serendipitous meetings and interactions. Density is not subordinate—conceptually or empirically—to interaction as some have suggested, and we thus do not make an empirical distinction between the two in this article. For instance, one might use transport systems as a measure of accessibility, but we would argue that it is unlikely that low-density living combined with good transport systems would have the same "buzz" (Storper and Venables 2004) as high-density locations.
- 3. Storper and Venables (2004, 353–54) differentiate between standard (codifiable) and tacit (noncodifiable) knowledge when they write:

Codifiable knowledge has a stable meaning which is associated in a determinate way with the symbol system in which it is expressed, whether it be linguistic, mathematical, or visual. Such information is cheap to transfer because its underlying symbol systems can be widely disseminated through information infrastructure, sharply reducing the marginal cost of individual messages.... By contrast, uncodifiable information is only loosely related to the symbol system in which it is expressed. This includes much linguistic, wordsbased expression. ... Bateson (1973) refers to the "analog" quality of tacit knowledge: communication between individuals which requires a kind of parallel processing of the complexities of an issue, as different dimensions of a problem are perceived and understood only in relation to one another. [Face-to-face] encounters provide an efficient technology under these circumstances, by permitting a depth and speed of feedback that is impossible in other forms of communication.

In addition, Allen (2000, 18) differentiates between the "codified knowledges embedded in the global networks identified by Manuel Castells" and "tacit knowledge production based upon convention and customary use."

4. Therefore, as explained by Kiesler and Cummings (2002, 67), geographically distributed collaborations such as email are not a substitute for physical proximity, especially in tasks where tacit knowledge is central, where work is uncertain, and where interactions need to coordinate interdependent groups. They write:

Today, one hears many stories of people forging close work relationships at a distance through electronic communication. Some researchers argue that over time, electronic communication allows for sufficient spontaneous communication to support the development of new close ties. . . . However, the evidence thus far suggests that physical proximity, with its many spurs to spontaneous communication, serves this purpose better. Work collaborations are more likely to be created and sustained, and are likely to be more satisfying and productive, than distributed (geographically distant) collaborations.

- This file has population data for metropolitan areas and their components for 1990 and 2000, using 1999 MSA definitions.
- 6. A number of important points need to be made clear about land area. First, it is assumed that the component land area (county, town, etc.) does not change much over time. Thus county or town land area data from the 2000 Census Factfinder are taken to pertain equally well to 1990. Changing much, however, are the MSA and PMSA definitions across years, in this case 1990 to 1999. These changes are primarily reflected in differences in the components that comprise the MSAs. Counties are often added and dropped from MSAs, and we have accounted for these changes in our calculations of MSA/PMSA land areas for these two years. In making these changes, two issues arose. First, in 1990, some regions were defined as an MSA, but in 1999 were subsumed under an existing MSA or Consolidated Metropolitan Statistical Area (CMSA). When this happened, we conclude that the MSA or CMSA existed in 1990 (without the subsumed MSA), and thus have them both included as data points in 1990. Second, in several cases, regions existed as CM-SAs in 1990, but then became MSAs in 1999. Given that

no new counties are added or dropped, we simply use the MSA definition for both 1990 and 2000.

- 7. As documented in the Fulton et al. (2001) report, urban land is defined by the NRI as a land cover/use category consisting of residential, industrial, commercial, and institutional land; construction sites; public administrative sites; railroad yards; cemeteries; airports; golf courses; sanitary landfills; sewage treatment plants; water control structures and spillways; other land used for such purposes; small parks (less than ten acres) within urban and built-up areas; and highways, railroads, and other transportation facilities if they are surrounded by urban areas. Also included are tracts of less than ten acres that do not meet the preceding definition but are completely surrounded by urban and built-up land. Two size categories are recognized in the NRI: areas of a quarter-acre to ten acres, and areas of at least ten acres. The authors' 1982 population data come directly from Census estimates, and their 1997 estimates are based on a straight-line interpolation of the 1990 and 2000 Census estimates. The authors also make use of New England County Metropolitan Area (NECMA) definitions for several New England regions including Boston, New London, CT; Hartford, CT; Springfield, MA; Lewiston-Auburn, ME; Pittsfield, MA; Portland, ME; Providence, RI; and Bangor, ME. Given that we use MSA/PMSA definitions in our data set, we are forced to use their NECMA estimates of density in our data set. More detailed information about their methodology is available in their report.
- 8. Comparing a metro's urban density across years gives an idea of the relative rates at which they are adding population and urban lands. If a metro is urbanizing land faster than it is adding population, its urban density will decrease across years. Conversely, if a metro adds population faster than urbanized land, urban density will increase across years. Also, a metro's marginal density will always be positive if it adds population, even when density decreases across years. Often when land is urbanized faster than population grows, however, marginal density will be small. High marginal densities, however, are often correlated with the size of the city, so that places that have already large population bases and that add more population might tend to have larger marginal densities. So, for an individual metro, more information is revealed by comparing the urban density measures across years. Finally, marginal density will be negative if a metro loses population.
- 9. This composite density measure is roughly in terms of standard deviations, with some values greater than zero and others less than zero. Subsequently, we interact this variable with another continuous variable, percentage creative employees in a PMSA. To ensure that each variable is on a similar scale (between 0 and 1), we rescale the composite density index such that all values are between 0 and 1, thus creating a variable that is similar in form to percentage creative employees. The rescaled density measure takes this form:

Composite Density + (- min CompositeDensity) (max CompositeDensity) + (- min CompositeDensity)

10. This measure includes the following occupations: education administrators, engineers, architects,

mathematical and computer scientists, natural scientists, postsecondary teachers, teachers except postsecondary, librarians, archivists, curators, social scientists, urban planners, writers, artists, entertainers, and athletes.

- 11. Dividing the high-tech percentage of metro output by the high-tech percentage of national output forms a location quotient (LQ) for a metro. An LQ of 1.0 means a metro's concentration of high-tech output is equal to the nation's concentration, although greater than 1.0 means a metro's concentration is higher than the nation's concentration.
- 12. Given our use of 1990 PUMS data, we are not able to recover the actual density of creative capital. Doing this would require that we obtain, for the numerator of a density measure, an absolute number of creative workers. Because the PUMS primary geographic unit, the Public Use Microdata Area (PUMA), often spills across numerous PMSAs, however, we are forced to exclude those PUMAs from a final total. Thus, we only use PUMAs that are entirely within a PMSA, clearly complicating any attempt to recover an absolute number of creative workers. The percentage of metro area employment that is creative is more appropriate because we assume that on average, the excluded PUMAs are not different than those included, and thus the percentage creative capital is approximately accurate. Finally, we can attempt to estimate the actual creative density, by multiplying the percent supercreative employment by 1990 population, and then dividing by 1990 Census land area. We did this, and note that its correlation with the creative-density interaction is r = 0.8707. We thus use the interaction term, because it enables use of our constructed composite density index.
- 13. Beyond the results reported in Table 5, we estimated several other regressions using proxies for patents as the dependent variable to test the consistency of the findings. When the 2000 Milken Tech-Pole Index and its components—the high-tech LQ and tech share—are inserted as dependent variables, the regression estimation results are very similar to those using patents as the dependent variables. The creative-density interaction is positive and significant in the Tech-Pole and tech share regressions, and positive and insignificant in the LQ regression. Next, we estimated regressions using citation-weighted and industry-weighted patents. The interaction term once again is positive and significant. Overall, these results provide additional evidence in support of the hypotheses. Also, we undertook several procedures to guard against the possibility that our results were determined or overly reliant on the presence of outliers and influential points. First, we took out the top 5 percent of the observations from 1999 patents/100,000 and the creativity-density interaction term. This resulted in twenty-two observations being removed from the data set. When the trimmed 1999 patents/100,000 is regressed on the trimmed interaction term and the other independent variables, we again observe a positive and significant coefficient on the creativity-density interaction term. Finally, the estimation results of an iteratively weighted least squares robust regression procedure also return a positive and significant coefficient on the interaction term.
- 14. When we remove creativity and creative density, the effect of bohemians on patents turns from negative to

positive, but remains insignificant. The effect of gays on patents had been positive but insignificant with creativity and creative density, and when we remove these two variables the effect of gays becomes significant.

- 15. Current empirical work, such as that by Duranton and Puga (2001) and Feldman and Audretsch (1999), looks at the role of diversity and city size on innovation, finding that larger, more diverse cities and regions are typically more innovative. Among many others, these researchers have probed this diversity–size relationship. Given the different focus of our research, we instead are interested in whether or not density and city size interact in some important way to promote innovation. As such, we include several preliminary empirical tests probing these effects.
- 16. An additional issue associated with metro size is that a critical mass or threshold of creative persons must be achieved before their presence can have any discernable effect on innovation. In other words, we would look to see whether the absolute number of supercreative employees matters more than the percentage, and also to see whether this critical mass predominates the effect of density. We felt that although this was an important issue, it was outside the scope of this study, and thus chose to pursue it at a later date.
- 17. By not using the weighted average density measure, however, and by using the PMSA as our unit, we are able to construct and use the composite density index. The value of this composite index was discussed earlier.

# References

- Allen, J. 2000. Power/economic knowledge: Symbolic and spatial formations. In *Knowledge*, *space*, *economy*, ed. J. Bryson, P. Daniels, N. Henry, and J. Pollard, 15–33. London: Routledge.
- Almeida, P., and B. Kogut. 1999. Localization of knowledge and the mobility of engineers in regional networks. *Management Science* 45:905–17.
- Andersson, R., J. Quigley, and M. Wilhelmsson. 2005. Agglomeration and the spatial distribution of creativity. *Papers in Regional Science* 84:445–64.
- Anselin, L., A. Varga, and Z. Acs. 2000. Geographical spillovers and university research: A spatial econometric perspective. Growth and Change 31:501–15.
- Asheim, B. 2000. Industrial districts: The contributions of Marshall and beyond. In *The Oxford handbook of economic* geography, ed. G. Clark, M. Gertler, and M. Feldman, 413–31. Oxford, U.K.: Oxford University Press.
- Audretsch, D., and M. Feldman.1996. R&D spillovers and the geography of innovation and production. *The American Economic Review* 86:630–40.
- Autant-Bernard, C. 2001. The geography of knowledge spillovers and technological proximity. *Economics of Innovation and New Technology* 10:237–54.
- Bathelt, H., A. Malmberg, and P. Maskell. 2004. Clusters and knowledge: Local buzz, global pipelines and the process of knowledge creation. *Progress in Human Geography* 28:31–56.
- Black, D., G. Gates, S. Sanders, and L. Taylor. 2000. Demographics of the gay and lesbian population in the

United States: Evidence from available systematic data sources. *Demography* 37:139–54.

- Bunnell, T., and N. Coe. 2001. Spaces and scales of innovation. *Progress in Human Geography* 25:569–89.
- Carlino, G., S. Chaterjee, and R. Hunt. 2001. Knowledge spillovers and the new economy of cities. Working Paper No. 01-14, Federal Reserve Bank of Philadelphia, Philadelphia, PA.
  - ——. 2007. Urban density and the rate of invention. Journal of Urban Economics 61:389–419.
- Caves, R. 2002. Creative industries: Contracts between art and commerce. Cambridge, MA: Harvard University Press.
- Ceh, B. 2001. Regional innovation potential in the United States: Evidence of spatial transformation. *Papers in Regional Science* 80:297–316.
- Chapple, K., A. Markusen, G. Schrock, D. Yamamoto, and Y. Pingkang. 2004. Gauging metropolitan "high-tech" and "i-tech" activity. *Economic Development Quarterly* 18:10–29.
- Ciccone, A., and R. Hall. 1996. Productivity and the density of economic activity. *The American Economic Review* 86:54–70.
- Cohen, W., and D. Levinthal. 1994. Fortune favors the prepared firm. *Management Science* 40:227–51.
- Currid, E. 2006. New York as a global creative hub: A competitive analysis of four theories on world cities. *Economic Development Quarterly* 20:330–50.
- Desrochers, P. 2001. Local diversity, human creativity, and technological innovation. *Growth and Change* 32:369–94.
- DeVol, R., P. Wong, J. Catapano, and G. Robitshek. 2001. America's high-tech economy: Growth, development, and risks for metropolitan areas. Santa Monica, CA: Milken Institute.
- Duranton, G., and D. Puga. 2001. Nursery cities: Urban diversity, process innovation, and the life cycle of products. American Economic Review 91:1454–77.
- Feldman, M. 2000. Location and innovation: The new economic geography of innovation, spillovers, and agglomeration. In *The Oxford handbook of economic* geography, ed. G. Clark, M. Gertler, and M. Feldman, 373–94. Oxford, U.K.: Oxford University Press.
- Feldman, M., and D. Audretsch. 1999. Innovation in cities: Science-based diversity, specialization and localized competition. *European Economic Review* 43:409–29.
- Feldman, M., and R. Florida. 1994. The geographic sources of innovation: Technological infrastructure and product innovation in the United States. *Annals of the Association of American Geographers* 84:210–19.
- Florida, R. 2000. Competing in the age of talent: Quality of place and the new economy. Pittsburgh, PA: Richard King Mellon Foundation.
  - ——. 2002a. Bohemia and economic geography. The Journal of Economic Geography 2:55–71.
  - ——. 2002b. The economic geography of talent. Annals of the Association of American Geographers 92:743– 55.
- ——. 2002c. The rise of the creative class. New York: Basic Books.
- —. 2005. The flight of the creative class. New York: HarperCollins.

- Florida, R., and G. Gates. 2001. *Technology and tolerance: The importance of diversity to high-technology growth.* Washington, DC: Brookings Institution, Center for Urban and Metropolitan Policy.
- Fulton, W., R. Pendall, M. Nguyen, and A. Harrison. 2001. Who sprawls most? How growth patterns differ across the U.S. Washington, DC: The Brookings Institution, Center for Urban and Metropolitan Policy.
- Gertler, M. 2003. Tacit knowledge and the economic geography of context, or the undefinable tacitness of being (there). *Journal of Economic Geography* 3:75–99.
- Glaeser, E. 2000. The future of urban research: Nonmarket interactions. Brookings-Wharton Papers on Urban Affairs 101–50.
- ——. 2005. Urban colossus: Why is New York America's largest city? Discussion Paper No. 2073, Harvard Institute of Economic Research, Boston.
- Griliches, Z. 1979. Issues in assessing the contribution of research and development to productivity growth. *The Bell Journal of Economics* 10:92–116.
- ——. 1990. Patent statistics as economic indicators: A survey. Journal of Economic Literature 28:1661– 1707.
- Hall, B., A. Jaffe, and M. Trajtenberg. 2001. The NBER patent citations data file: Lessons, insights, and methodological tools. NBER Working Paper 8498, National Bureau of Economic Research, Cambridge, MA.
- Hamilton, L. 1992. Regression with graphics: A second course in applied statistics. Belmont, CA: Duxbury Press.
- Hipp, C., and H. Grupp. 2005. Innovation in the service sector: The demand for service-specific innovation measurement concepts and typologies. *Research Policy* 34:517– 35.
- Jacobs, J. 1961. The death and life of great American cities. New York: Random House.
- ——. 1969. The economy of cities. New York: Random House.
- Kiesler, S., and J. Cummings. 2002. What do we know about proximity and distance in work groups? A legacy of research. In *Distributed work*, ed. P. Hinds and S. Kiesler, 57–80. Cambridge, MA: MIT Press.
- Lang, R., and K. Danielsen. 2005. Review roundtable: Cities and the creative class. *Journal of the American Planning Association* 71:203–20.
- Lee, S. 2001. Innovation, human capital, and diversity. Working Paper, H. John Heinz III School of Public Policy and Management, Carnegie Mellon University, Pittsburgh, PA.
- Lee, S., R. Florida, and Z. Acs. 2004. Creativity and entrepreneurship: A regional analysis of new firm formation. *Regional Studies* 38:879–91.
- Lucas, R. 1988. On the mechanics of economic development. Journal of Monetary Economics 22:3–42.
- Markoff, J. 2005. What the dormouse said: How the 60s counterculture shaped the personal computer. New York: Penguin.
- Markusen, A., and D. King. 2003. The artistic dividend: The arts' hidden contributions to regional development. Minneapolis: Project on Regional and Industrial Economics, Humphrey Institute of Public Affairs, University of Minnesota.

- Marshall, A. 1920. Principles of economics. London: Macmillan.
- Milligan, M. 2003. The individual and city life: A commentary on Richard Florida's "Cities and the creative class." *City and Community* 2:21–26.
- Ó hUallacháin, B. 1999. Patent places: Size matters. Journal of Regional Science 39:613–36.
- Ó hUallacháin, B., and T. Leslie. 2005. Spatial convergence and spillovers in American invention. *Annals of the Association of American Geographers* 95:866–86.
- Pinch, S., and N. Henry. 1999. Paul Krugman's geographical economics, industrial clustering and the British motor sport industry. *Regional Studies* 33:815–27.
- Piore, M., and C. Sabel. 1984. The second industrial divide: Possibilities for prosperity. New York: Basic Books.
- Porter, M. 1998. Clusters and the new economics of competition. *Harvard Business Review* November– December:77–91.
- Romer, P. 1990. Endogenous technological change. *Journal* of Political Economy 98:S71–S102.
- Sawicki, D. 2003. Review: The rise of the creative class. APA Journal 69:90–91.
- Saxenian, A. 1994. Regional advantage: Culture and competition in Silicon Valley and Route 128. Cambridge, MA: Harvard University Press.
- Scherer, F. M. 1983. The propensity to patent. International Journal of Industrial Organization 1:107–28.
- Scott, A. 2000. The cultural economy of cities. London: Sage. \_\_\_\_\_\_. 2005. On Hollywood. Princeton, NJ: Princeton University Press.
- Sedgely, N., and B. Elmslie. 2004. The geographic concentration of knowledge: Scale, agglomeration, and congestion in innovation across U.S. states. *International Regional Science Review* 27:111–37.

- Sonn, J. W., and M. Storper. 2003. The increasing importance of geographical proximity in technological innovation: An analysis of U.S. patent citations, 1975–1997. Paper presented at the What Do We Know About Innovation? Conference, University of Sussex, Brighton, U.K.
- Storper, M. 1997. The regional world: Territorial development in a global economy. New York: Guilford.
- Storper, M., and A. Venables. (2004). Buzz: Face-to-face contact and the urban economy. *Journal of Economic Geography* 4:351–70.
- Strumsky, D., J. Lobo, and L. Fleming. 2005. Metropolitan patenting, inventor agglomeration and social networks: A tale of two effects. Los Alamos National Laboratory Technical Report LAUR-04-8798, Los Alamos National Laboratory, Los Alamos, NM.
- Thompson, W. 1965. A preface to urban economics. Baltimore: Johns Hopkins University Press.
- Trajtenberg, M. 1990. A penny for your quotes: Patent citations and the value of innovations. *The Rand Journal* of Economics 21:172–187.
- U.S. Census Bureau. 2007a. www.census.gov/population/ cen2000/phc-t3/tab01.txt (last accessed 11 May 2007).
   2007b. www.factfinder.census.gov (last accessed 11 May 2007).
- U.S. Patent and Trademark Office. 2007. http://www.uspto. gov/web/offices/pac/doc/general/index.html#patent (last accessed 29 August 2007).
- WebCASPAR. 2007. Caspar.nsf.gov (last accessed 11 May 2007).
- Zucker, L., M. Darby, and M. Brewer. 1998. Intellectual human capital and the birth of U.S. biotechnology enterprises. *American Economic Review* 88:290– 306.

*Correspondence:* H. John Heinz III School of Public Policy and Management, Carnegie Mellon University, Pittsburgh, PA 15213–3890, e-mail: knudsen@andrew.cmu.edu (Knudsen); Martin Prosperity Institute, Rotman School of Management, University of Toronto, 101 College Street, Suite 420, Toronto, Ontario, Canada M5G 1L7, e-mail: Florida@rotman.utoronto.ca (Florida); Kevin.Stolarick@rotman.utoronto.ca (Stolarick); The Williams Institute, UCLA School of Law, 405 Hilgard Ave., Box 951476, Los Angeles, CA 90095, e-mail: gates@law.ucla.edu (Gates).