Driving Regional Innovation

The Innovation Index 2.0

August 2016

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KELLEY SCHOOL OF BUSINESS
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Indiana Business Research Center

Driving Regional Innovation

The Innovation Index 2.0

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Introduction

Without data, you are just another person with an opinion.

What drives regional competitiveness and economic performance? How does one measure competitiveness? This report answers these questions by presenting the Innovation Index 2.0, a web-based tool that provides innovation-related data. The data that comprise the index are motivated by an extensive review of the literature. We provide a rationale for the county-based measures of both input and outputs of innovation. Many items included in the index measure innovation activity over time and across regions.

Background

The Innovation Index provides the user relevant measures of innovation and regional competitiveness that are constructed based on research pertaining to the forces and prerequisites of competitiveness and performance. The importance of clusters to regional economic growth has been well documented elsewhere.[1] The regional competitive model that is advocated here focuses on the regional character of internally generated (i.e., internal to the region) growth through innovation and entrepreneurship. Put differently, fresh ideas and a propensity to take chances provide a fertile seedbed for innovation and a foundation to create new economic opportunities.

The Innovation Index provides a set of analytic tools that can help regional leaders reach a strong consensus on regional strategic direction. Turning the opening sentence about data on its head, one can use data and analytical tools as corrective lenses to see and understand a region's weaknesses, strengths and potential. In this way, data and analysis can inform stakeholders' collective action toward a common vision and can guide complex decision-making at a regional-level.

It is not surprising that developing data-driven regional development strategies requires data. The Innovation Index consolidates data from several public sources. Economic development theory and empirical analysis help to answer why some phenomena or outcomes are important enough to bother collecting data for. For example, why is it

[1] For example, see Porter, M. (2003). The economic performance of regions. *Regional studies*, 37(6–7), 545–546.

that risk taking is important? Why is online agriculture considered important for economic growth? Why would a regional innovation index include net migration patterns, the number of STEM graduates or foreign direct investment attractiveness?

The Innovation Index web tool also provides the user with the ability to create a region county-by-county. If, for example, one wants to augment the official four counties of the Davenport-Moline-Rock Island (Quad-Cities) metropolitan statistical area (MSA) to include Clinton and Muscatine counties as the relevant region for the Quad Cities First Regional Development Association, one can easily do so.

A vast majority of the data items used for the Innovation Index is county-based and can be downloaded by county, MSA, other official statistical area and state. The website aggregates the data items in an equal, unprejudiced manner. That is, the data are assembled thematically and with no judgment calls regarding what measures are the most relevant in terms of measuring innovation capacity.

Version 2.0

The Innovation Index 2.0 expands on the previous index by adding more than 50 new measures. Like the first version, these data are all at the county level and can be aggregated at the regional level based on the user's needs. These measures reflect contemporary research on understanding and measuring innovation. For example, the new version of the Innovation Index includes measures that take into account regional knowledge spillovers, technology diffusion and foreign direct investment. The ***Innovation 2.0 Data Set*** that serves as the foundation for the index and its many components and building blocks has a significantly longer time series of data items than the previous index. With the new longitudinal data, there are several new measures of change over time.

As with version 1.0, the measures that make up the single headline index are organized into indexes based on broad themes or related concepts. Like the earlier version, these indexes are also designated as either an input—human capital, for example—or output—for example, patents—to innovation.[2]

Finally, version 2.0 includes a "for the first time" index for social capital. Social capital has increasingly captured the attention of many academics and social scientists. Some economists hypothesize that social capital—a critical component of which is trust—helps provide the social relationships and networks that foster economic growth.

[2] Slaper, T. F., Hart, N. R., Hall, T. J., & Thompson, M. F. (2011). The index of innovation: A new tool for regional analysis. *Economic Development Quarterly*, 25(1), 36–53.

Because it is so new and in its relative infancy, the supporting theoretical discussion for including social capital as a measure, and indeed how to measure it, is given special treatment. The companion articles and documentation can be found at www.statsamerica.org/ii2/reports.

Organization of the Report

This report first provides an overview of how the index is constructed, what it includes and how it is calculated. Next, the major index categories are described in detail, including the basis for why the individual measures were chosen and specifics regarding how they are calculated. The following section provides some guidance on how to interpret the index results. Finally, a conclusion summarizes the main findings and offers suggestions for further research.

Calculating the Innovation Index

The Innovation Index provides policymakers and economic development practitioners with a unique web-based tool for exploring regional innovation performance and comparing that with the United States, a state or other regions. The index culminates in a top-level “headline” number that includes both innovation inputs and outputs in order to measure both innovation capacity and output potential. However, one can drill into the major index categories to explore a region’s assets or liabilities in detail.

This section of the report overviews the major index categories and how they are calculated. (More specifics regarding the individual measures included in the index are presented in the next section.)

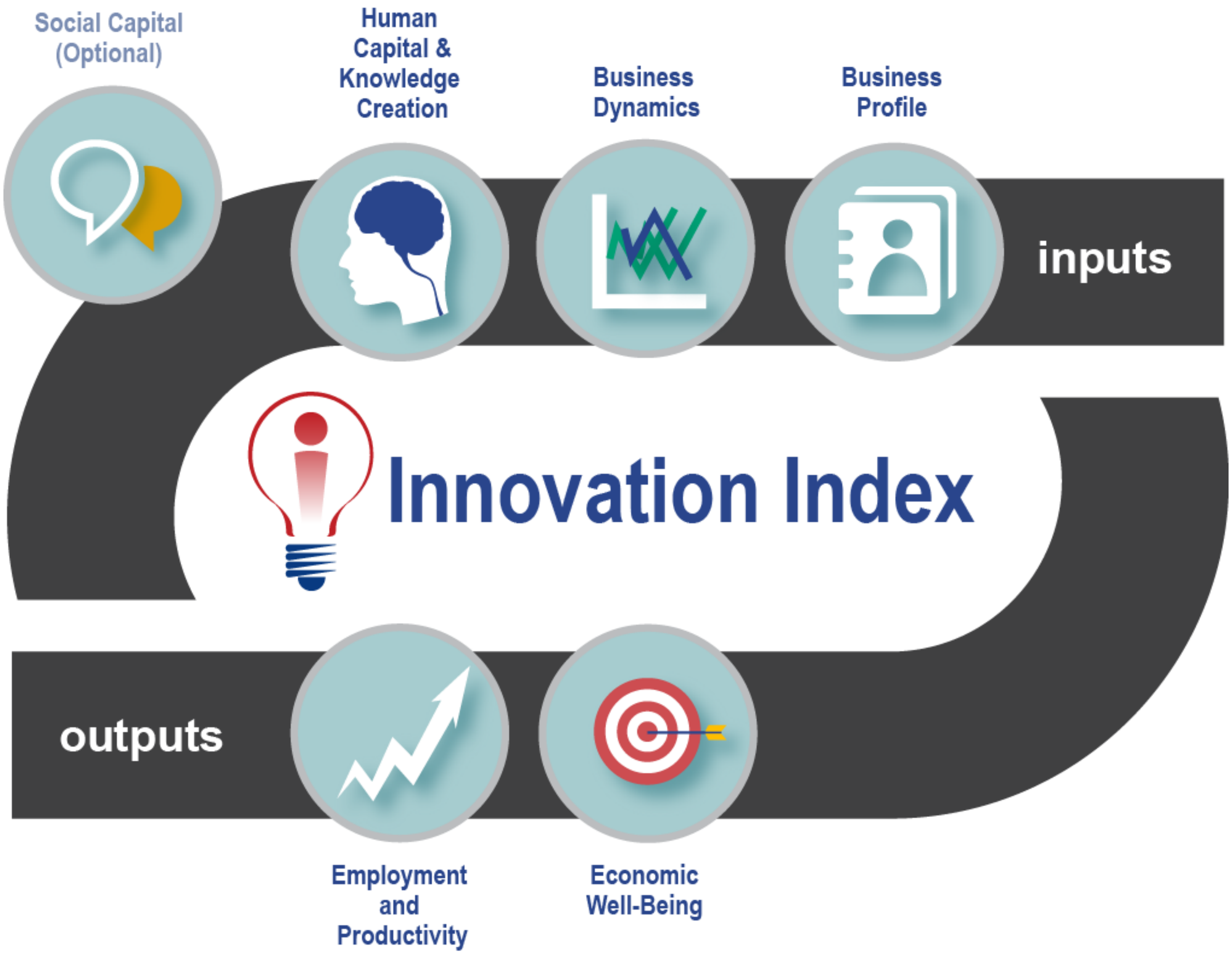
Index Composition

As illustrated in **Figure 1**, the headline Innovation Index is calculated from five major index categories (three based on innovation inputs and two based on innovation outputs). The structure and the calculation of the index is hierarchical, or built up pyramid-like, from a large foundation of data to the single headline index. The “headline” index—the one, high-level summary index—is comprised of five major categorical indexes organized thematically. Those five major indexes are built up from several core indexes that are built up from several measures that are also organized thematically along more precisely defined concepts. Those measures are directly tied to the data.

One of the new features in this version of the index is that users may also include the optional Social Capital Index in the calculation of the overall index.

An additional State Context category is displayed as part of the data output. It is for reference only and not included in the calculation of the overall index because many regions, official or user-defined, cross state boundaries. It includes measures that are important but not available at the county level.

Figure 1: Innovation Index Composition



Source: Indiana Business Research Center

Inputs

Inputs are those factors, influences or conditions that promote innovation and create knowledge. Input measures are categorized into three thematic categories:

- The **Human Capital and Knowledge Creation Index** suggests the extent to which a region's population and labor force are able to engage in innovative activities.
- The **Business Dynamics Index** gauges the competitiveness of a region by investigating the entry and exit of individual firms—the creative destruction measures.
- The **Business Profile Index** measures local business conditions and resources available to entrepreneurs and businesses.

Table 1 lists the individual measures contained within these three indexes. Each measure is scaled to the U.S. value and weighted equally (accounts for one share of the index calculation).

Table 1: Innovation Input Measures

Core Index	Measure
Human Capital and Knowledge Creation Index	
n/a	"Salad Days" Population, Ages 25-44, Annual Average Growth Rate
Educational Attainment	High School Attainment, Population Ages 18–24
	Some College, Population Age 25+
	Associate Degree, Population Age 25+
	Bachelor's Degree, Population Age 25+
	Graduate Degree, Population Age 25+
Knowledge Creation and Technology Diffusion	Patent Technology Diffusion
	University-Based Knowledge Spillovers, Science and Engineering
	Business Incubator Spillovers
STEM Education and Occupations	STEM Degree Creation
	Technology-Based Knowledge Occupation Clusters
	High-Tech Industry Employment Share
Business Dynamics Index	
Establishment Formation	Establishment Births to Total Establishments
	Traded Sector Establishment Births to Total Establishments
	Jobs Attributed to Births to Total Employment
	Change in Establishment Births to Total Establishments
Establishment Dynamics	Establishment Expansions Divided by Contractions
	Establishment Births Divided by Deaths
	Traded Sector Establishment Dynamics
Venture Capital Dollar Measures	Average Annual Venture Capital
	Venture Annual Capital by Expansion Stage
	Venture Annual Capital by High-Tech Industry
	Change in Venture Capital
Venture Capital Count Measures	Initial Public Offerings (IPOs)
	Average Annual Venture Capital Deals
	Change in Venture Capital Deals

Core Index	Measure
Business Profile Index	
Foreign Direct Investment Attractiveness	FDI Employment Index, Foreign Source
	FDI Employment Index, National Source
	FDI Investment Index, Foreign Source
	FDI Investment Index, National Source
Connectivity	Density of Residential Fixed High-Speed Connections
	Average Annual Change in Residential Fixed High-Speed Connections
	Online Agriculture
Dynamic Industry Profile	Average Small Establishments
	Average Large Establishments
	High-Tech Industry Early-in-Life-Cycle Establishment Ratio
Proprietorship	Proprietorship Rate
	Change in Proprietorship Rate
	Proprietor Income to Wages and Salaries Ratio
	Availability of Capital from All Banks

Source: Indiana Business Research Center

Outputs

Outputs are the direct outcomes and economic improvements that result from innovation inputs. Output measures, as shown in **Table 2** are divided into two categories:

- The **Employment and Productivity Index** describes economic growth, regional desirability or direct outcomes of innovative activity.
- The **Economic Well-Being Index** explores standard of living and other economic outcomes.

Table 2: Innovation Output Measures

Core Indexes	Measure
Employment and Productivity Index	
n/a	Job Growth to Population Growth Ratio
n/a	Change in Share of High-Tech Industry Employment
Industry Performance	Cluster Diversity
	Cluster Strength
	Cluster Growth Factor
Gross Domestic Product (GDP)	GDP per Worker

	Change in GDP per Worker
Patents	Change in (Average) Patenting Rate
	Patent Diversity
	Patents by Institution Type*
Economic Well-Being Index	
n/a	Per Capita Personal Income Growth
Compensation	Annual Wage and Salary Earnings per Worker Growth
	Change in Proprietors' Income per Proprietor
n/a	Income Inequality–Mean to Median Ratio
n/a	Average Poverty Rate
n/a	Average Unemployment Rate
n/a	Dependency Ratio–Measured by Income Sources
n/a	Average Net Migration

* This measure is descriptive, so it is presented for information, but not included in the index calculation.
Source: Indiana Business Research Center

Social Capital

The **Social Capital Index** suggests the regional benefits of collaborative networks that undergird a community's ability to meet its challenges. It is an optional component that users may choose to include or exclude in the index calculation. This index is optional for several reasons.

1. The theory and conceptual framework is still in flux and development. In addition, the role that social capital may have in economic performance has not been precisely described or well established.
2. The data that can be conceptually attached to social capital is relatively thin. While official statistics may serve as proxy data in many cases, the qualitative nature of social capital makes collecting robust data difficult. For example, trust is a core concept—if not the defining concept—of social capital. Yet it is measured only periodically by surveys that often have few respondents for less densely populated states.
3. Consistent time series data for many social capital concepts simply doesn't exist.
4. Finally, the notion of social capital may not be well understood or embraced by economic development practitioners. Why mandate that the headline index include elements that are not desired?

Table 3 lists the individual measures contained within the Social Capital Index.

Table 3: Social Capital Index Measures

Core Index	Measure
Social Capital Index	
Altruism	Literacy
	Local Radio Media
	Outreach
	Philanthropy
	Volunteering, Individual Participation
Formal Membership and Participation	Organizational Memberships, Non-Rent Seeking
	Organizational Memberships, Rent Seeking
	Political Participation–Active
	Political Participation–Voting
Informal Interaction	Home Ownership
	Household Composition (Non-Family Residents)
	Local to Traded Industry Ratio
	Neighborhood Identity, Arts and Culture
	Patent Collaboration Density
	Residential Stability
	Single-Parent Households
	Suicide Rate
Shared Norms	Foreign Born
	Foreign-Born Naturalized Citizens
	Ideological Homogeneity
	Median Age
	Non-English Speakers at Home
	Political Homogeneity
	Racial Diversity
	Religious Homogeneity
	Socioeconomic Inequality (Gini Coefficient)
	Youth and Senior Population
Trust	Crime–Property
	Crime–Violent
	Governance
	Trust–Generalized
	Trust–Institutional

Source: Engbers, Trent A., Michael F. Thompson, and Timothy F. Slaper. "Theory and Measurement in Social Capital Research. "*Social Indicators Research*, March 2016. Available at http://link.springer.com/article/10.1007/s11205-016-1299-0?wt_mc=internal.event.1.SEM.ArticleAuthorOnlineFirst and http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2653794.

State Context

The **State Context** category is not included in the calculation of the overall index since data are not available at the county level. Nevertheless, measures in this section, shown in **Table 4**, are important to understanding innovation and are sometimes used for state-level innovation measures. As a result, the web tool provides these data at the state level for users to explore.

Table 4: State Context Measures

State Context
Per Pupil Education Spending in K-12
Science and Engineering Graduates from State Institutions
STEM Talent Flow
Total R&D Expenditures as a Percentage of GDP
R&D Spending by Universities and Private Firms Per Capita
Industry-Performed R&D as a Percentage of Industry Output
Federal Expenditures for Academic and Nonprofit R&D Per Capita
University R&D Expenditures in Science and Engineering Per Capita
Industry Funding of Academic Research Per Capita
State Funding of Academic Research Per Capita
Institutionally-Based Startups
Small Business Innovation Research and Technology Transfer Awards
Kauffman Entrepreneurship Index
Establishment Entry Rate
Establishment Survival Rate
Volunteer Rate

Source: Indiana Business Research Center

Index Calculation

The Innovation Index headline number combines the five major categorical indexes presented above. Following the method of the previous Innovation Index, each major thematic input index is weighted equally, by 20 percent each. The Employment and Productivity Index is weighted 30 percent and Economic Well-Being is weighted 10 percent. If the Social Capital Index option is selected, the economic well-being and social capital indexes are each weighted 10 percent. There is a two-fold rationale for this: 1) Social capital is not as well developed as a concept and there is scholarly debate about how to measure its many facets. 2) The elements of economic well-being are not as directly related to innovation capacity or innovation outcomes as the other categorical indexes. For example, personal income can be augmented by government transfer payments and have nothing to do with a region's dynamism. In addition, regions that have experienced a natural resource boom would register high rates of job and wage growth, painting an overly rosy picture of the region's innovative activities. Finally, the index values for economic well-being across counties also tend to be higher than the other categorical indexes, largely because there is less dispersion in measures like poverty rate and average unemployment than there is among measures like high-tech employment or R&D expenditures among counties.

However, the index values or scores are not derived in the same manner as with the first innovation index. In the first iteration, the indexes were constructed in a very straight-forward manner using the value for the nation as the benchmark "100" value. In short, the values for a particular measure were divided by the national value.

The Innovation Index 2.0 expanded the set of measures enormously, but the downside to a more comprehensive set of measures is that there are many empty cells (lots of zeros) and also many cases of wildly large outliers. If the simple index calculation described above were used, some index values would top 14,000, for example, venture capital in the Bay Area. Index values that register somewhere in the thermosphere are not particularly helpful. In order to make regional comparisons viable at all, we used a method to scale the data in a fashion that maintained the rankings between regions using a continuous scale. For those measures for which the data have extreme outliers or many zeros (e.g., over 2,500 counties have zeros values for venture capital), the U.S. benchmark index value deviates from 100, sometimes significantly.

The method we used was to transform every variable to a normal distribution. This method prevented any given measure or variable from exceeding 200, and kept the rank ordering of regions according to higher or lower raw values. Here is a summary of the procedures used to calculate the index:

- Invert the four "bad" indicators so that high values for, say, poverty rate will receive a low measure value.
- Transform all series to a normal distribution, maintaining zeros and nulls as zeros and nulls. Applying the transformation to zeros/nulls will score those data to values greater than the negative values in the data array, which is unreasonable.
- Create indexes by dividing all cell values by 0.5 (the mean for a normal distribution) and multiplying by 100. For any measure, this will create an array of values between 0 and 200.

- Excluding true zeros and nulls, for values less than 100, apply the “ratchet 50” transformation so that no index values fall below 50. (For index values below 100, the “ratchet 50” is the sum of the index value and 100 and divides the sum by 2. Index values over 100 remain as they are.) This technique doesn’t affect any rank ordering. It only keeps the index scores between 50 and 200 for the non-zero cases.

These procedures maintain rank ordering for any particular year and keep the extreme cases within range. This does not allow for consistent year-over-year changes in the index for a particular geographic definition. Intra-temporal comparisons (i.e., comparisons within the same year) between the same regional units of analysis (i.e., counties, metros, economic development districts) are still valid. It is *invalid* to compare a county unit of analysis with a metropolitan statistical area (MSA), for example, as they are two different geographic units of analysis. Performance, or progress toward a goal, can be measured over time using changes in the individual measures for a particular geographic unit.

Understanding the Index

Indexes attempt to present complex data simply, somewhat like a dashboard gauge. Understanding what the dashboard is showing may require interpretation. The headline, categorical and core indexes score a region or county on a continuous scale. Users may prefer to compare their regions of interest against other benchmark or peer regions that share characteristics like population density, access to transportation infrastructure or presence of federal research laboratories.

Additionally, the headline index has no simple, unambiguous definition because, at the time of this writing, there is no established statistical relationship between the indexes and desired outcomes.[3] Rather, the headline index is a collection of measures—both input and output—baked into one at-a-glance number. The headline index is an aggregation of underlying major index categories for innovation inputs and outputs. Traditionally, inputs and outputs would not be combined into a single figure. One might suggest that higher levels of innovation inputs would result in higher levels of outputs—they would move together—but it should be acknowledged that the headline index is an aggregation of many contrasting parts that may or may not move in tandem.

[3] The Innovation Index version 1.0 did show a statistical relationship between innovation inputs and outputs but version 2.0 contains many more measures and this general relationship may not hold. See page 90 in the prior report: www.statsamerica.org/innovation/reports/sections2/4.pdf.

The measures for inputs and outputs in the headline and major index categories are theoretically linked, as discussed below. The fact that the data that measure innovation inputs and outputs in an earlier version of the index tend to move together offers statistical support for joining the two concepts into a single composite, headline index.

In-Depth Exploration of the Innovation Index Components

This section breaks down each of the major index categories (except Social Capital), describing why the measures were chosen and how they are calculated. More details on the calculations are available in Appendix A beginning on page 90. The optional Social Capital Index is discussed in detail in a separate report. Social capital warrants a separate and special treatment. As noted above, the theory, measurement of and data for social capital is not as well developed as the concepts and measures of other components of the index. In the coming years, social capital as a discipline will likely undergo many changes. Rather than having this document rapidly go out of date, a better outcome would be to update the social capital documents over time.

Human Capital and Knowledge Creation Index

Human capital and knowledge creation affect the degree to which a county's labor force is able to engage in innovative activities. Growth in a county's workforce ages 25 to 44 signifies that a county is becoming increasingly attractive to younger (arguably more energetic) workers—those more likely to contribute to innovation. Counties with high levels of human capital are those with enhanced knowledge, measured by educational attainment, patent diffusion, knowledge spillover, business incubator presence, STEM degree holders and occupations, and the share of high-tech employment. Higher levels of human capital are associated with higher levels of innovation and faster diffusion of technology.

This category has been extensively modified since the prior version of the Innovation Index. All of the measures except for population growth rate, technology-based knowledge occupation clusters, and high-tech industry employment share are new to version 2.0 of the index.

"Salad Days" Population Annual Average Growth Rate

Measure: "Salad Days" Population is the annual average growth rate for the population ages 25 to 44 from 2002 to the latest year available.

Rationale: While a growing population is desirable, growth in the number of newborns or retirees does little to suggest whether those people most likely to engage in innovative activities are present in the community. For this reason, population growth rates are confined in the index to ages 25 to 44. The lower bound ensures transient college students become less of a factor in influencing the overall rate of growth, whereas the upper bound signifies a point at which a professional's geographic location would likely remain more stable. Those in the 25-to-44 age bracket are likely to be less risk averse and more entrepreneurial. Moreover, population growth in this age bracket suggests the possibility that new residents are likely to augment the innovative and entrepreneurial characteristics of the base community.

References are available on page 65 and the equation on page 91.

Educational Attainment

A common measure of human capital is educational attainment. Educational attainment measures can reflect the quantity (e.g., average years of schooling) or quality (e.g., average SAT score) of educational attainment. Researchers often combine quantity and quality educational attainment indicators in an attempt to more accurately capture the knowledge and skill level of a population. Educational attainment likely contributes to firm and regional innovation capacity by providing general and specific knowledge and skills that facilitate the creation, diffusion, and adoption of new technologies and other innovations. The Innovation Index includes measures for high school attainment and postsecondary education.

High School Attainment

Measure: High School Attainment is the percent of population ages 18 to 24 years with a high school diploma.

Rationale: Working-age adults need a minimum of a high school diploma to compete in today's workforce. Without it, they face greater employment challenges and economic hardship than those with a high school diploma or higher. Some argue that lacking a high school diploma bars individuals from entering the middle class. Those without a high school diploma are further limited to strictly low-skill jobs.

McDaniel and Kuehn (2012), in their empirical study of the employment outcomes of non-high school graduates ages 18 to 22 in the U.S. find that high school dropouts work significantly fewer hours and have lower earnings than their high school graduate counterparts. Others have reported that young high school dropouts are half as likely to be employed as those with a bachelor's degree or higher. McDaniel and Kuehn (2012) point out that the transition period from high school to young adulthood is especially important for those who do not pursue higher education, citing research from Raaum and Røed (2006) that suggests that this period is critical for "establishing and maintaining sustained connection to work." A precarious position in the job market makes becoming and remaining financially independent more difficult for high school dropouts. Bridgeland et al. (2006) report that high school dropouts were more than three times as likely to be unemployed than college graduates in 2004. Between the ages of 16 and 24, an estimated four in 10 adults without a high school diploma received some form of government assistance in 2001. Studies also reveal that high school dropouts are more likely to engage in criminal activity, use drugs and tobacco, and report poor mental health.

The consequences of dropping out of high school do not stop at the individual. Communities and nations suffer from fewer skilled and productive workers to fuel economic activity and innovation. Higher dropout rates correspond to more crime, as well as public health and other social concerns. Government resources may need to be redirected from economic activities to support a growing need for government assistance when unemployment levels are high.

References are available on page 66 and the equation on page 91.

Postsecondary Education

Measures:

- Some College: Percent of population ages 25 and older with some college, but no degree
- Associate Degree: Percent of population ages 25 and older with an associate degree
- Bachelor's Degree: Percent of population ages 25 and older with a bachelor's degree
- Graduate Degree: Percent of population ages 25 and older with a graduate, professional or other post-bachelor's degree

Rational: The research team included multiple measures for postsecondary education in order to capture the relative importance of the knowledge differential, together with regional distinctions in the types of degrees earned. In many states, educational funding mechanisms favor four-year universities, whereas elsewhere state policy tends to favor two-year community colleges and vocational schools.

An important educational differential is also present within states and counties where higher concentrations of bachelor's degree graduates tend to be located in and around metropolitan areas, whereas associate degree concentrations tend to be elevated in more rural counties—where fewer residents have the resources or ability to travel to distant four-year institutions. Community colleges and vocational schools are more widely dispersed and proximate to rural residents. They also tend to provide education at a lower cost, with easier access, and tend to offer more flexible course schedules, such as evening or weekend courses. Community colleges are also more likely to cater to a region's economic development needs than larger universities.

The Organization for Economic Cooperation and Development (OECD) report, "Tertiary Education: Developing Skills for Innovation and Long-Term Growth in Canada," summarizes the larger economic and social benefits of education:

> Education can lift the quality of labour and raise economic performance through its effects on the pace of technological change, the adoption of more innovative and productive work practices, labour-market participation and managerial quality. Education can also contribute to equality of opportunity and promote broader benefits through lower crime, improved health outcomes and greater social cohesion (Cheung, Guillemette, & Mobasher-Fard, 2012, p. 5).

A recent review of the literature on the impact of postsecondary education on economic development suggests that the proportion of workers with tertiary education tends to increase the likelihood of technological uptake and adaptation. Crescenzi (2005), in his examination of the relation between innovation and growth in Europe, finds evidence that human capital accumulation, defined as tertiary educational attainment, may offset the negative effects of low geographic accessibility in peripheral regions.

Several empirical studies have also examined the relation between firm-level innovation and the educational background of company managers and founders. Studies focused on management characteristics in established firms suggest that manager education level is a significant internal factor of firm-level innovation capacity and can influence the research and development (R&D) investment–financial leverage relationship important for continued innovation. Research on the link between founder education and innovation is less straightforward. Concerning entrepreneurs of established firms, Heunks (1998) finds that innovation activity is more dependent on a founder's educational background in small firms than in large firms. In new startups, Arvanitis and Stucki (2012) provide evidence that education level is one of three main characteristics of founders that contribute to startup innovation activity. Other research reveals an association between the formal education of CEOs and firm innovation activity.

References are available on page 66 and equations on page 91.

Knowledge Creation and Technology Diffusion

Generating and applying knowledge creates new possibilities for innovative products and services. Measures of patent diffusion and university R&D spending in science and engineering fields, as well as the presence of business incubators, are used as indicators of knowledge creation and technology diffusion at the county level. This core index explores how innovation and resources for innovation travel from one county to another. These measures take into account how likely a technology is to spread and how knowledge resources spread to neighboring regions.

Patent Technology Diffusion

Measure: Patent Technology Diffusion measures the degree to which a technology spreads and is adopted. The diffusion score is based on a region's volume of patents and the technology classes of those patents (based on data from the U.S. Patent and Trademark Office—see **Table 6** in Appendix A). The measure, while original, is based on the academic work discussed below.

Rationale: The number of patents is an established measure of regional innovation. New patents predict subsequent patenting and births of new industries, and other indexes have used it to measure innovation. Patents lead to economic growth because knowledge related to patents is shared across networks and spreads to neighboring regions. Research focusing on inventors has found that this diffusion of knowledge relies on tight and close networks. However, not all patents are diffused easily and, therefore, not all patents are useful predictors of regional innovation.

Indeed, the complexity of patent knowledge affects both the strength and distance of knowledge diffusion. Controlling for other important factors, patents with moderate knowledge complexity have an overall higher probability of being cited, especially by proximate actors. While simple knowledge diffuses to both local and distant actors, it has less potential for a breakthrough; however, complex knowledge resists diffusion altogether. Hall et al. (2001) conducted similar research looking at patent originality and generality. Generality measures how widely a patent is cited across classes, and originality measures how widely the patent quotes previous patents across classes.

Using these concepts, our goal with this measure is to approximate patents with moderate complexity by giving high scores to patents that use a wide range of previous knowledge and are generalizable to a wide audience. The concentration of patents with high scores for generality and originality in a region will, therefore, predict future patents and increase innovation in that same area.

References are available on page 67 and the equation on page 92.

University-Based Knowledge Spillovers, Science and Engineering

Measure: University-Based Knowledge Spillovers are calculated using university research and development (R&D) spending and distance between the university and the county or region selected. We incorporated only the R&D spending in the following fields: engineering, geosciences, life sciences, math and computer science, and physical science. Higher scores will represent regions close to universities with high R&D spending in science and engineering fields.

Rationale: This measure estimates how scientific knowledge spreads from universities to neighboring regions. At a local level, academic R&D positively affects new firm formations, industry R&D and other measures of innovation and economic development. However, not only do universities lead to innovation locally, but they can also affect economic development in neighboring counties and states. Previous research looking at knowledge spillovers has concentrated on the effects of industry R&D on innovation in neighboring regions. However, because universities are less competitive and less profit driven than industries, their knowledge should spread more widely across institutions and regions. Indeed, knowledge from universities can travel through social ties, meetings and informal contacts.

At the state level, one would expect that university R&D expenditures could predict a state's level of patenting. Previous research has also tried to find a way to quantify the spillover distance of knowledge from universities. While Jaffe (1989) finds little evidence of university knowledge spillover, more recent studies find an effect of university R&D on innovation across geographic locations. Anselin, Varga and Acs (1997) find that university R&D and the decay parameter for distance both positively affect knowledge creation, and that university R&D spillover extends over 50 miles. Woodward et al. (2006) find that the optimum radius for the effect of university R&D on new plant formation is 60 miles. However, when looking at different industries, this radius ranges from 15 to 85 miles. Counties within a certain mile radius of a university with larger R&D expenditures will, therefore, receive valuable knowledge for innovation.

In order to measure university knowledge creation, we look at the R&D expenditures in departments relevant to the industry: environmental sciences, life sciences, math and computer sciences, physical sciences, and engineering. These departments are similar to those used by Woodward et al. (2006). However, we added geosciences as it is both a prominent and profitable scientific field. In order to measure the geographic component of knowledge spillover, we weight R&D spending by the distance between counties or regions.

References are available on page 68 and the equation on page 94.

Business Incubator Spillovers

Measure: Business Incubator Spillovers are akin to university knowledge spillovers. Incubators offer services to new business in the surrounding area and help them survive and succeed. This measure calculates a score using the number of business incubators within 50 miles, weighted by distance. Higher scores represent regions with greater concentrations of business incubator resources.

Rationale: Previous research has found that business incubators provide a helpful environment for new businesses. Business incubators provide cheap space, business advice and networking opportunities for startups, which reduces startup costs (or accelerates the process). However, the empirical findings vary on the actual effect and on the mechanisms through which incubators lead to more economic development. Studies comparing incubators have found that screening practices and the focus on either local markets or high-value services might affect outcomes. Moreover, some studies find that university incubators or the proximity to a university lead to greater knowledge flows, while others find that for-profit incubators are more efficient. Grimaldi and Grandi (2005) argue that regions need diversity in the type of business incubators in order to help a variety of businesses. Both nonprofit and for-profit incubators are included in the Innovation Index data and are expected to have a positive impact on the region's innovativeness and economic well-being.

We expect business incubators to have an effect not only on businesses in the same county but also in neighboring regions. Indeed, because knowledge transfers through social ties, meetings and informal contacts, we expect business incubators to have an effect across institutions and regions—similar to university and industry R&D. However, because business incubators offer some services that are space dependent, their effect will not be as strong as R&D spillover. Therefore, our decay function for the effect of the number of incubators decreases at a faster rate.

References are available on page 70 and the equation on page 95.

STEM Education and Occupations

Workers in STEM occupations drive innovation, productivity and competitiveness. An educated STEM workforce is critical to the development of new technology and innovation. STEM workers find ways to increase productivity, generate new ideas and technology, and start new companies. Individuals with STEM degrees, on average, enjoy higher earnings than individuals with degrees in non-STEM fields, and STEM workers are also less likely to experience joblessness than their non-STEM counterparts. Higher educational attainment in STEM fields is well recognized as an important component of economic development.

STEM Degree Creation

Measure: STEM Degree Creation calculates the number of STEM degree graduates (at the bachelor's, master's and doctorate level) per 1,000 individuals from institutions of higher learning located in the county or region, averaged across the last three years available.

Rationale: For years, scholars and policymakers have acknowledged that the U.S. economy needs more people with advanced STEM degrees. While the total number of bachelor's degrees awarded annually in the U.S. has nearly tripled over the past 40 years, the number of STEM degrees has grown at a much slower pace. At the same time, STEM occupations are projected to grow by approximately 17 percent from 2008 to 2018, compared to a projected growth rate of only 10 percent for non-STEM occupations. And while many if not most STEM graduates will not remain in the region after graduating, the presence of STEM programs at universities provides some indicator of the science and engineering activities in the region.

A caveat: Given the focus on the contribution that STEM degree holders can make to innovation at the national, regional or local level, it becomes important to consider the nationality or visa status of STEM graduate students. About 35 percent of STEM master's students and about 50 percent of STEM Ph.D. students are temporary U.S. residents. Furthermore, almost three quarters of electrical engineering and two-thirds of industrial engineering doctorates are awarded to foreign students. Due to immigration restrictions or personal preference, many of them return to work in their home countries. In contrast to the large share of international students in STEM graduate programs, 95 percent of STEM bachelor's degree graduates are U.S. citizens. However, 74 percent of them do not attend graduate school in STEM fields, and of those who enter the job market, 25 percent work in non-STEM related tasks (Atkinson & Mayo, 2010).

References are available on page 72 and the equation on page 95.

Technology-Based Knowledge Occupation Clusters

Measure: Technology-Based Knowledge Occupation Clusters measures the concentration of jobs that apply high tech (e.g., scientists and engineers) based on the employment share relative to total employment.

Rationale: Richard Florida (2004; 2005) developed the notion of the "creative class," a social concept that describes a region's population by identifying the types of occupations in the workforce. Like Florida, the research team hypothesized that there is a certain occupational mix that favors innovative behaviors. We substituted eight technology-based knowledge occupation clusters that are similar in composition to those used by Henderson and Abraham (2004), who sought to explain the agglomeration effect of knowledge occupations at the county-level.

References are available on page 72 and the equation on page 96.

High-Tech Industry Employment Share

Measure: The High-Tech Industry Employment Share of total employment measures high-tech in terms of industries rather than occupations. This measure captures the share of employment in these industries and, thus, their relative importance. While high-tech industries are predominantly in manufacturing, the definition also includes research and development companies and engineering firms.

Rationale: In addition to high-tech, specialized knowledge occupations, such as scientists or engineers, there are other complementary occupations linked to high-technology firms and activities. These complementary occupations within high-tech industries can provide opportunities for the regional labor force and even serve as a magnet, attracting new talent to a region. According to Kolko (1999), high-tech firm employment and growth is overwhelmingly found in urban centers, producing a rural-urban technology gap.

Together with the aforementioned technology-based knowledge occupational data, this high-tech industry employment measure sheds light on the extent to which a region's occupational and industry mix provide the existing capacity to generate innovative products and processes. The measure also signals the region's ability to augment local innovative capacity by attracting new firms and new talent.

References are available on page 72 and the equation on page 98.

Business Dynamics Index

Business dynamics in the form of entry and exit is the mechanism by which outdated ideas and industry practices are replaced by new and potentially revolutionary ones. This process of creative destruction—a term and concept introduced by the economist Joseph Schumpeter—is the hallmark of a thriving and dynamic economy. This dynamic is at the heart of competition—creating new industries, invigorating old ones and relegating inefficient practices to the pages of history. As such, exit and entry drive the growth and prosperity of individual firms, as well as the economy at large. This is a central focus of research in both economics and management.

In particular, an expanding body of research focuses on the geographic dimension of entry and exit, the effect on the formation and growth of firms, and the associated implications for local and national economies. As older, inefficient and marginally productive capital is destroyed, new, efficient and productive capital is created. This implies that productivity variability is likely linked closely to job reallocation, as workers matched with unproductive capital lose their jobs and new, more productive couplings of labor and capital are made.

This major index category is completely new to version 2.0 of the Innovation Index. While the prior version did include a measure of establishment churn and one for venture capital, version 2.0 explores those concepts in detail using an assortment of new measures.

Establishment Formation and Dynamics

Establishment Formation

- Establishment Births to Total Establishments charts the creative side of the Schumpeter ledger by measuring how many new business locations are formed.
- Traded Sector Establishment Births to Total Establishments measures which new businesses serve "export" markets, i.e., sell to those outside of the region rather than serving the local population.
- Jobs Attributed to Births to Total Employment measures the number of jobs that new businesses created.
- Change in Establishment Births to Total Establishments compares the rate of business formation over time. If the establishment birth rate is declining, it signals a potentially less dynamic business environment.

Establishment Dynamics

- Establishment Expansions Divided by Contractions is the ratio of businesses that are increasing employment vs. businesses that are reducing employment.
- Establishment Births Divided by Deaths signals the degree to which new businesses are replacing businesses that are dying.
- Traded Sector Establishment Dynamics measures whether the businesses that serve distant markets—in contrast to the local markets—are, on balance, growing or declining. It is calculated as the sum of births and expansions divided by the sum of deaths and contractions.

Rationale: Some researchers have emphasized technological and knowledge requirements that have changed, or even destroyed, the economic viability of a region's industries, firms and jobs. But then again, these changes also present the opportunity to create new industries, firms and jobs. Labor churn improves productivity. Labor churn is an indicator that members of the workforce are bettering their employment situation. That is, workers move to more desirable and higher-wage jobs. In the same way, churn—whether measured by new businesses being established or by existing businesses expanding their workforce—provides an indicator that the region is undergoing positive economic change.

Several measures for churn have been proposed in the literature, each with some theoretical rationale. For example, focusing on establishments, if one holds to the creative destruction view of economic dynamism, then one might propose a measure that subtracts deaths from births and divides by the total number of all establishments. Or, if one wants to include all types of dynamic establishments that persist but are growing (creative) or shrinking (destruction), then one might add births, deaths, expansions and contractions together and divide by the total number of establishments. Arguably, if one were more interested in entrepreneurship, it is only establishment births made by a new enterprise (in contrast to an expanding company increasing its number of outlets) as a proportion of all establishments that matters.

There are also churn measures that focus on employment, not establishment, counts.

In recent decades, the U.S. economy has shown secular declines in employment and business dynamics. This decline in dynamism has been well documented in the analysis of job creation rates, job destruction rates and startup entry rates. Decker et.al (2014a) note that while the job creation rate averaged 18.9 percent in the late 1980s, it declined to an average 15.8 percent for the 2004–2006 period preceding the Great Recession. Similarly, the job destruction rate fell from 16.1 percent in the late 1980s to 13.4 percent in the mid-2000s. Furthermore, Hyatt and Spletzer (2013) find evidence that the decline in employment dynamism has accelerated since 1998.

While the levels of each measure vary across sources depending on the scope and the definition used in the configuration of the relevant database, scholars find consistent downward trends in employment and business dynamics indicators. In their 2012 paper, Reedy and Strom find downward trends since the 2000s for job creation rates, business survival rates and business births (among others).

These findings contrast with the work of Hathaway, Schweitzer and Shane (2014) who focus on the rise in the number of new establishments opened by existing businesses (outlets). While they recognize the declining rate of new firm formation and the declining contribution to employment by new firms, they notice a simultaneous rise in new outlet formation and in the job creation rate at new outlets. Thus, establishment formation may—yea verily does—overstate the entrepreneurial dynamic because establishment births don't measure business formation exclusively. Rather, the measure melds business formation and business outlet expansion together.

The Great Recession elicited a wealth of research on the effects of the recession on employment and business dynamics statistics. Economic theory suggests that recessions are periods of accelerated productivity-enhanced reallocation or "cleansing." Foster, Grim and Haltiwanger (2013) found that job creation fell much more dramatically than in prior recessions and job destruction increased less than in prior recessions. Even though productivity-enhancing reallocation was more intense in previous recessions, reallocation in the late 2000s was still productivity enhancing since less-productive establishments were more likely to exit, while the more-productive establishments were more likely to grow. Haltiwanger, Jarmin and Miranda (2011) who also focus on the 2008–2009 recession notice that in comparison to the modest declines in job creation from startups in previous recessions, there were very large declines in job creation from startups between 2006 and 2009. Both of these papers suggest a decline in overall churn, which Lazear and Spletzer (2012) highlight as important because it represents the movement of workers to higher-valued uses. They estimate the value of reduced churn during the last recession to be approximately $208 billion (or 0.4 percent of GDP for a period of 3.5 years).

Given the wealth of research published in recent years on this topic, it is surprising to notice the lack of regional research and the lack of understanding on what is driving this decline in business dynamics. Hathaway and Litan (2014) are among the few that study the issue of declining dynamism from a regional perspective. They find that the downward trend in business dynamics is pervasive across all 50 U.S. states and in over 300 metropolitan areas since 1978. Decker et al. (2014a) find that the changing firm age distribution—more mature firms—explains a great deal of the slower pace of business dynamics. They also find that changes in the U.S. industrial composition (a shift from manufacturing to retail) that would tend to accelerate the pace of business dynamics has not done so. Instead, the industries that are expanding, like services, are increasingly mature, signaling a decline in business dynamism.

References are available on page 73 and equations on page 100.

Venture Capital

Dollar Measures:

- Average Annual Venture Capital for a region are averaged over 10 years and scaled by the region's average GDP for the time period.
- Venture Annual Capital by Expansion Stage focuses on expansion stage funding in the region, averaged over 10 years and scaled by the region's average GDP.
- Venture Annual Capital by High-Tech Industry focuses on VC funding for firms in high-tech, averaged over 10 years and scaled by the region's average GDP.
- Change in Venture Capital measures the trend in a region's venture capital dollar financing, comparing the 2000–2003 average with the average of the latest four years of available data.

Count Measures:

- Initial Public Offerings sums the total number of IPOs in a region over the last 10 years and scales that figure by the region's average GDP.
- Average Annual Venture Capital Deals sums the total number of venture capital deals and scales that figure by the region's average GDP.
- Change in Venture Capital Deals measures the trend in the number of a region's venture capital deals, comparing the 2000–2003 average with the average of the latest four years of available data.

Rationale: Venture capital (VC) funds are used to launch new ideas, commercialize a new technology or expand innovative companies. Funds are provided by investors to startup firms and small businesses with perceived long-term growth potential. For startups that do not have access to capital markets, this may be the only option to enter a market. It typically entails high risk for the investor, but it has the potential for above-average returns. Venture capital can also include managerial and technical expertise. Most venture capital comes from a group of wealthy investors, investment banks and other financial institutions that pool such investments or partnerships. This form of raising capital is popular among new companies or ventures with limited operating history, which cannot raise funds by issuing debt. The downside for entrepreneurs is that venture capitalists usually get a say in company decisions, in addition to a portion of the equity.

Version 1 of the Innovation Index included a measure of average venture capital since 2000. However, the research team updated this measure to reflect a more complex relationship between venture capital and innovation. In version 2.0, venture capital data are presented in greater detail to provide the user a sense of the overall levels of VC, as well as to provide a sense of a region's specialization and the degree to which a region may be "up and coming" given early stages of VC financing. IPOs are also of potential interest in that the financial flows to the firm's founders may find their way back into the region, both in terms of charitable giving and new business ventures.

Existing empirical research on venture capital and innovation points to a positive and significant relationship; however, debate exists over its relative strength and causal direction. Industry-level analyses generally show that increases in VC activity are associated with higher levels of innovation, as measured by patents and total factor productivity (TFP) growth. At the level of the individual firm, VC-backed companies have higher TFP growth in the years prior to obtaining VC financing, and obtaining venture capital is associated with continued higher TFP growth. Companies that have more patents also obtain more VC investment. A conclusion some have reached is that VC tends to finance firms with above-average levels of innovation rather than making the firms more innovative.

In the United States, venture capital may be responsible for up to 14 percent of all innovative output activity. VC investment firms are highly selective with their investments to maximize the probability of high returns. The return on venture capital, and possibly its importance, is diminished somewhat by the fact that the VC investments are typically management-intensive. Looking for VC funding may consume a considerable level of effort by the seeking firm's management, just as VC firms exert considerable effort seeking suitable projects to invest in.

References are available on page 74 and equations on page 103.

Business Profile Index

What is the business environment of a region? The Business Profile Index attempts to gauge this by measuring local business conditions and resources available to entrepreneurs and companies. The components identify the possible resources a region might offer that can lead to growth and subsequent innovation. These resources can be found in the form of capital (foreign investments or local banks), connectivity within and with other regions, dynamism of region and entrepreneurship.

Is the region attractive to investors? Foreign direct investment measures the degree to which foreign or domestic companies are investing in the region relative to a U.S. average. Connectivity includes both broadband density and penetration, and the percentage of farmers conducting business online. Proprietorship is a rough measure of entrepreneurial activity and signals the degree to which workers may have migrated from working in a "safe" job in a large, established company to the "gig economy." Entrepreneurs as well as businesses on Main Street need access to capital and the availability or lack of local funding may make or break an otherwise viable startup. Finally, the research team incorporated measures of average small establishments, average large establishments, and a measure of the proportion of small firms in high-tech industries that are, likely, early in their life cycle. This last measure was created to respond to recent literature on industry life cycles and compares the values for each industry to the national average in order to detect which regions are growing in exceptional ways.

Except for the measures on broadband density and establishment size, this index boasts all new and expanded content.

Foreign Direct Investment Attractiveness

Measures:

- FDI Employment Index, Foreign Source, is a ratio of employment created by new, foreign-sourced greenfield investment to the working-age population (between ages 18 and 66).
- FDI Employment Index, National Source is a ratio of employment created by new, U.S.-based incoming greenfield investment to the working-age population.
- FDI Investment Index, Foreign Source, is a ratio of the most recent three-year average of dollars of greenfield investment by new, foreign-sourced FDI to the working-age population.
- FDI Investment Index, National Source, is a ratio of the most recent three-year average of dollars of greenfield investment by new, U.S.-sourced FDI to the working-age population.

Rationale: Foreign direct investment (FDI) flows are relevant to innovation for at least two reasons. First, there is a transfer of knowledge, technology and know-how when an outside firm enters a regional market or adds to the production portfolio of that region. Second, it says something about the openness of a region's economy and community and whether a region is "business friendly." A possible third benefit is that many FDI greenfield investments represent large expenditures, showing that the incoming firm is either expanding or restructuring to improve productivity. Foreign direct investment is a completely new measure in our index but is often used in measuring innovation.

Foreign direct investment increases competition and gives rise to positive technological externalities and spillovers, thereby raising dynamic efficiency. Subsequently, communities welcome FDI through tax breaks and training assistance. Researchers have measured the amount of knowledge transfer and spillovers, and have found benefits in backward linkages. Often these studies look at FDI impacts in developing countries since those effects are more observable; however, even multinational firms that invest in the U.S. experience knowledge spillovers both from and to the investing firm. The knowledge spillover/transfer can happen in multiple ways: demonstration effects, worker mobility and vertical linkages. Demonstration effects occur when the host country's firms mimic and reverse engineer a multinational firm's products and practices. Worker mobility or turnover occurs from the multinational firm training its employees then subsequently losing them to startups, other businesses or entrepreneurial ventures. Vertical linkages with multinational firms cause increased local firm productivity due to knowledge spillovers.

Determining a quantitative measure of the knowledge spillover/transfer from FDI is difficult—hence numerous proxies are typically used to assess the influence exerted by FDI. One plausible explanation for the diverse conclusions from various FDI spillover studies is that countries and firms within countries might differ in their ability to benefit from the presence of foreign-owned firms and their superior technology. The ability for technology spillovers to occur may be attributed to the degree of absorptive capacity of the firm or region. While it may be difficult to ascertain a universal relationship of FDI on host countries, often multinational firms do bring new jobs and capital investments to their new location.

Within our Innovation Index, the FDI data are related to greenfield investments and plant and equipment expansions. This concept does not include the majority of FDI flows that are related to mergers and acquisitions. These data are announced FDI investments that may or may not be realized. The data are treated, however, as though all announcements are realized.

References are available on page 74 and equations on page 107.

Connectivity

Connectivity is a driver of innovation, helping entrepreneurs and businesses remain relevant and competitive in the information age. Broadband capacity and Internet access for agricultural operations serve as indicators of an area's level of technology adoption.

The Internet helps connect businesses and individuals regionally and globally. Adopting higher technology and embracing new business models embodied by Internet connectivity signals the degree to which a region has, on average, the capacity to expand business opportunities and lower transactions costs. Innovation, the uptake of new technology and access to resources—be they natural, financial or talent—are linked to widespread Internet usage for individuals and businesses. As a result, the Innovation Index reports both a snapshot of the current "state of the art" connectivity capacity and speed of a region, as well as the overall trend of the average household adopting high-speed Internet connections.

Broadband density and penetration was included in the prior version of the Innovation Index, though it has been modified due to improved data availability. For version 2.0, we have added online agriculture to account for the use of the Internet specifically in this sector.

Broadband Density and Penetration

Measures:

- The Density of Residential Fixed High-Speed Connections is a snapshot measure, and at the time of this writing, defined as residential fixed high-speed connections of at least 3 mbps downstream and at least 768 kbps upstream per 1,000 households. The snapshot measure will undergo definitional changes as technology changes. The measure will adopt the latest definition of the upper end of broadband capacity as defined, collected and reported by the Federal Communications Commission (FCC). The technology has and is expected to rapidly change, so only the last year of available data is used. Given that the primary application for the index is inter-region, the changing definition over time is inconsequential.
- The Average Annual Change in Residential Fixed High-Speed Connections is measured by the change in residential fixed high-speed connections over 200 kbps in at least one direction per 1,000 households from 2009 to the latest year available. This trend measure attempts to track the adoption or diffusion of a standard broadband speed measure over time.

Rationale: Several state-level studies have attempted to capture the effect of adding broadband capacity to a region's infrastructure. These studies suggest that broadband capacity has an overwhelmingly positive impact on economic performance.

Broadband provides high-speed Internet connections to businesses and consumers. Thus, high-speed Internet access ensures that businesses and individuals can access and share new ideas from virtually any location. An increase in broadband density would indicate an improvement in capacity over time.

References are available on page 75 and equations on page 109.

Online Agriculture

Measure: Farm Operators with Internet Access is the percentage of farms that use the Internet to conduct business.

Rationale: Farm businesses stand to benefit from the adoption of computer technology and the Internet. Farmers who use the Internet to manage and improve operations have a competitive edge over farmers who do not, and they may be more innovative than their peers.

The degree to which farmers take advantage of Internet and computer resources increases their chance of success in the new economy. Fortunately, more and more farmers each year are turning to personal computers and the Internet to help manage, improve and expand their farm business. In 1999, only 29 percent of farmers reported having access to the Internet. In 2013, this number rose to 67 percent. Internet usage by farmers offers a number of potential benefits. For example, the Internet provides farmers access to current and comprehensive information (e.g., weather, government regulations) and opportunities for collaboration with peers. Information technology is expected to become more important for farmers, and it is predicted that farmers will increasingly seek IT applications that support various aspects of farm operations.

Most of what we know about farmer computer and Internet usage comes from U.S. surveys of farmers located in the Great Plains, Ohio, California and Hawaii. This research shows that farmers who use the Internet do so for a variety of reasons, including communicating via email, processing business transactions, gathering information, and maintaining business websites. The studies reveal that a number of farm/farmer characteristics and other factors influence farmers' adoption of the Internet and computer technology. Farmer age and education-level are identified as important factors in most studies. Older and less-educated farmers are found to be less likely to adopt computers and use the Internet than their younger, more-educated peers. They also tend to incorporate fewer applications of the computer in their businesses than their peers.

Farm size (e.g., acres and sales), ownership of farm-related nonfarm business, farmer off-farm business income, and regional farm location are among the other relevant factors identified in the literature. Off-farm exposure to computer use through friends, family, education and employment is also found to encourage computer and Internet use by farmers. Smith et al. (2004) find that computer exposure is actually more influential than farmer age and farm size, two of the more common findings in studies of farmer computer and Internet use.

Interestingly, computer and Internet usage by farmers is associated with higher complexity and greater sophistication in farm business and farm management. We consider that it is possible that with greater complexity and sophistication comes greater innovation as well. Thus, following Atkinson and Nager (2014), we include a measure comprised of the percentage of farmers with Internet access.

References are available on page 75 and the equation on page 111.

Dynamic Industry Profile

The Dynamic Industry Profile Core Index includes measures of establishment size and early-in-life-cycle high-tech establishments. The strength of a region's profile hinges on a number of conditions.

Measures for the number of small businesses and large businesses per 10,000 workers are carried forward from the prior version of the Innovation Index, but we have expanded these measures by including data on early-in-life-cycle establishments in high-tech industries.

Average Small Establishments

Measure: Average Small Establishments measures the number of small establishments with less than 20 employees per 10,000 workers from 2002 to the latest year available.

Rationale: Small firms, it can be argued, are highly adaptable and can easily change their processes to incorporate new ideas. In recent years, high merger rates between small and large firms have coincided with increased technological influence of small firms. Some evidence, however, suggests these acquisitions may not be significant sources of innovation for large firms.

References are available on page 76 and the equation on page 112.

Average Large Establishments

Measure: Average Large Establishments measures the number of large establishments with 500 employees or more per 10,000 workers from 2002 to the latest year available.

Rationale: Theoretically, a higher proportion of large businesses would positively contribute to innovation through the increased availability of funds for research and development, as well as the resources to directly employ scientists rather than hire out research services. Available data, however, do not identify whether, or the degree to which, an establishment is engaged in innovation activities. It may be that one establishment has a large, low-skilled operation while innovative activities for the same firm occur at a different location.

Moreover, using data on large establishments, defined as establishments with 500 or more employees, may be of limited utility for explaining innovative capacities in rural counties with small economies. Not many large establishments exist in rural counties. Just the same, because the measure has some theoretical merit, the number of large establishments per 10,000 workers remains in the index.

References are available on page 76 and the equation on page 112.

High-Tech Industry Early-in-Life-Cycle Establishment Ratio

Measure: High-Tech Industry Early-in-Life-Cycle Establishment Ratio measures the relative youth of high-tech firms in the region. It is calculated by comparing the proportion of small, high-tech firms in a region relative to the national proportion for high-tech. A value of 1 indicates that the region has a similar number of small firms relative to the nation for each high-tech industry present in the region.

Rationale: Clusters of innovative activity are closely tied to the stages of an industry's life cycle. The propensity to innovate varies depending on if the industry is in a birth, growing, maturing or declining stage. Specifically, during the early stages of an industry life cycle, there is an increase in the entry of new firms and a high amount of innovative activity.

During the early stages of an industry life cycle, new and smaller businesses have an advantage: they are better at utilizing R&D resources and turning them into innovative activity. Research shows that the type of innovation depends on how a firm is able to absorb knowledge. It is important to look at clusters of small firms, especially in the high-tech industry sectors, to understand and predict where innovation comes from. Not only do small firms incorporate R&D, but they are able to utilize knowledge from other small firms. Indeed, in the first stages of the industry life cycle, there are more inter-industry spillovers. Therefore, it is important to have a cluster of small firms in a variety of industries to encourage knowledge sharing and more innovations.

In addition to the distinction made between new firms, establishments and outlets, researchers have emphasized the difference between *small* and *young* firms. Until recently, research on employment and business profiles provided great attention to the role of small businesses in the U.S. economy. It was often argued that small businesses were the primary source of job creation. Today, however, much more attention and recognition is given to the contribution of young firms to job creation.

In 2011, Neumark, Wall and Zhang found, without consideration for firm age, an inverse relationship between net growth rates and firm size based on the National Establishment Time Series (NETS). They concluded that small firms contributed disproportionately to net job growth. Two years later, Haltiwanger, Jarmin and Miranda (2013) got access to firm age data and found that, controlling for firm age, there is no systematic relationship between firm size and growth.

Reedy and Strom (2012) follow this age-focused trend by studying young firms by their age cohorts. They find that while young firms (and establishments) that survive their first two years continue to grow and add new jobs, the rate of their employment addition has been declining for business cohorts since 1994. But this is not the whole story. While most startups exit within their first 10 years, and firms that survive remain small, a small fraction of young firms become high-growth firms, making a substantial contribution to job creation. In fact, approximately 20 percent of U.S. gross job creation is attributed to business startups and 50 percent of job creation is attributed to high-growth firms—which are disproportionately young. Along the same lines, DynEmp, a new OECD project on the dynamics of employment, highlighted that firms five years of age or younger were the primary source of job creation in 18 countries throughout the 2000s due to the role of startups and high-growth young firms.

References are available on page 76 and the equation on page 112.

Proprietorship

Entrepreneurship is a complex, multifaceted concept and, in an ideal world, there would be a census of entrepreneurs to gauge the true concentration of those who drive business formation. Many definitions exist and multiple aspects of entrepreneurship are recognized in the literature. Researchers, depending on their conceptualization of entrepreneurship, tend to study either entrepreneurship's characteristics (e.g., innovation and growth) or outcomes (e.g., ownership and value creation).

Given the lack of consensus on how to measure entrepreneurship and that a headcount of entrepreneurs is not available, we use proprietorship as a proxy. Proprietorship captures the ownership aspect of entrepreneurship. It does overstate entrepreneurial activity, however. An entrepreneur would not likely purchase a hair salon or carpet cleaning franchise that has been in business for decades, while a proprietor who is interested in being one's own boss would. Entrepreneurs are dependent on capital to create and develop new businesses. Therefore, also included is a measure of local availability of capital. If a region contains many banks that are spending their funds locally, entrepreneurs will be more able to receive loans for their projects.

Proprietorship Rate

Measures:

- Proprietorship Rate is calculated by dividing the number of nonfarm proprietors by the total number of employed individuals. This measure also provides the extent to which the region's population is self-employed.
- Change in Proprietorship Rate measures the five-year change in the proprietorship rate, showing whether proprietorship has increased or decreased. This measure is something of a proxy for entrepreneurship, which is presumably stronger in places where proprietorship is increasing.

Rationale: Researchers commonly rely on self-employment and proprietorship rates in studies of entrepreneurship due to the availability and consistency of state and national data. Research using U.S. data suggests that proprietorship is associated with greater job growth and that this effect is stronger for metropolitan counties and in times of national economic expansion. Romero and Martínez-Román (2012), exploring the determinants of innovative proprietorship, identify three levels of key factors influencing innovation in small business: the personal characteristics of the self-employed individual, the characteristics of the organization and the characteristics of the external environment.

Time series data are preferred in studies of entrepreneurship as self-employment due to the apparent lag effect of self-employment on various economic variables of interest (such as wage and salary employment growth). It is common for proprietorship rates to be lagged for econometric analysis. Studies employing proprietorship rates show a preference for the use of nonfarm proprietorship data over total proprietorship data, although explanations vary.

In regard to the study of entrepreneurship and its connection to innovation, the use of the proprietorship rate is not without its limitations. All proprietors are not necessarily entrepreneurs in the traditional sense. A proprietor does not need to operate or manage her own business to qualify as such for tax purposes, nor is it the case that all proprietors have created what they claim today to be their business. Proprietors who are entrepreneurs are also not necessarily innovators. Unfortunately, it is impossible to tease out innovative entrepreneurs from non-innovative entrepreneurs using proprietorship data. Proprietorship data includes part-time business owners, "hobby" business owners, as well as proprietors that double as wage and salary employees. Additionally, these measures do not account for the continuation or dissolution of proprietorships. Thus, the rate of proprietorship does not differentiate between new and old entrepreneurial activity, nor does it differentiate between innovative and non-innovative entrepreneurial ventures.

References are available on page 77 and equations on page 114.

Proprietor Income to Wages and Salaries

Measure: The Proprietor Income to Wages and Salaries Ratio simply divides proprietor income by total wages and salaries in a region. A high regional ratio would suggest the presence of profitable entrepreneurial activity, which may also indicate a more dynamic and innovative economy.

Rationale: One way to gauge the success of entrepreneurial activity within an area is to compare proprietors' earnings (i.e., entrepreneur income) to total wages and salaries (i.e., employee income).

Research shows that U.S. proprietors earn less on average than wage and salary workers, and this finding holds regardless of county type (i.e., metropolitan, micropolitan or rural). According to one report, between 1998 and 2000, U.S. proprietors earned 30 percent less than wage and salary workers, with proprietors earning 70 cents per wage and salary dollar. Still, entrepreneur income does vary considerably across the United States. High-earning entrepreneurs tend to cluster around certain parts of the country, including south of the Mississippi River Valley, West Virginia, southern California, the Greater Chicago area, southeastern Wisconsin and the mid-Atlantic region.

The proprietor-employee earnings gap can partly be explained by the fact that many Schedule C filers (i.e., individuals reporting sole proprietorship earnings for tax purposes) report income earned from quasi-employment and side-business activities, which may be pursued in addition to traditional employment. The literature on the nexus between entrepreneurship and innovation recognizes that entrepreneurial types do exist and differentiates between their economic contributions. It is clear that not all entrepreneurs are innovators, though many innovators are entrepreneurs. Lifestyle entrepreneurs, for instance, may operate small-scale businesses for the purpose of sustaining themselves, which would not necessarily add to the local economy in terms innovation, employment and productivity. In contrast, high-growth entrepreneurs are more likely to strive for greater wealth and to engage in innovative activity to achieve this end. High-growth entrepreneurs are also more apt to employ a greater number of people, contribute more to their communities via taxes, and so on. Although some research suggests that high-growth entrepreneurs are more important to the economy, others have found that a high number of all entrepreneurial types, whether innovative or imitative, is sufficient to positively impact economic growth.

Other factors related to economic dynamics, such as the rate and quality of innovation in the area, may also help to explain earning differences between entrepreneurs (i.e., proprietors) and traditional employees. High proprietor income relative to wage and salary income may indicate a higher concentration of innovative entrepreneurial activity, or suggest more enduring and/or lucrative entrepreneurial activity in general. In more rural areas, high ratios may reflect an increase in self-employment due to a loss in manufacturing employment rather than the presence of innovative entrepreneurship.

References are available on page 78 and the equation on page 115.

Local Availability of Capital

Measure: Availability of Capital from All Banks is the local deposit share for all banks in the region as a proxy for local lending. This measure takes the sum of all deposits in all branches of a bank within a specified area divided by the sum of the corresponding institution deposit totals.

Rationale: Local banks are more likely to lend to smaller firms, startups and firms that do not have an established track record. Areas with higher concentrations of local bank deposits are more likely to exhibit greater rates of entrepreneurship, small and medium-sized enterprise activity, innovation, and growth than areas where there is little to no local banking activity.

Access to financing is one of the biggest issues facing aspiring entrepreneurs and small and medium-sized enterprises (SMEs). Anecdotal evidence and research suggests that small firms have the greatest difficulty in securing formal sources of external financing, while larger firms with a longer track record face fewer financing obstacles. Small firms are also more likely to be constrained in their operation and growth due to a lack of financing than larger firms.

SMEs account for the majority of the private sector in the United States; thus, addressing the financial constraints of SMEs is critical. It is said that lessening financial constraints through local financial development can support entrepreneurship, new firm formation, and an area's overall economic success. A large body of research supports the conclusion that financial development contributes to economic growth, at least in the long term, by fostering innovation and encouraging an efficient allocation of resources. Supporting research shows that reduced access to external financing is linked to lower growth, and that this effect is more pronounced for smaller firms. Access to external financing is also associated with greater firm innovation, including the introduction of new products and technologies, knowledge transfers, and new production processes.

SMEs face significant financial constraints in part due to the fact that many small firms do not have an established track record. (The cases of insufficient financial data are ironically called "informationally opaque" in the literature.) Small businesses receive less credit from large and foreign banks than firms that easily satisfy financial data requirements. Insufficient data firms also tend to have closer lenders, suggesting that distance from lenders is more of an impediment to SMEs. Local intermediaries are often better at overcoming the costs associated with screening and monitoring borrowers, and small banks are more apt to lend to startups and small businesses. Local lenders are also in a better position to obtain “soft” information about SME borrowers.

This measure for local capital availability is in some flux. Early attempts to develop strict measures for local capital resulted in extremely sparse data, and as a result, the research team temporarily abandoned one local measure. In future updates of the index, we intend to follow Adelino, Ma and Robinson (2014) in measuring financial resources as the share of local bank deposits relative to all deposits in a particular geographic area. Given that local banks are more likely to lend to smaller firms, startups and SMEs, areas with higher concentrations of local bank deposits are more likely to exhibit greater rates of entrepreneurship, SME activity, innovation and growth in comparison to areas where there is little to no local banking activity. Please consult future footnotes for changes to this measure.

References are available on page 78 and equations on page 115.

Employment and Productivity Index

This index describes economic growth, job growth, regional desirability and the direct outcomes of innovative activity. Measures in this index suggest the extent to which local and regional economies are moving up the value chain by producing more sophisticated and differentiated products and are increasing the high-value talent pool.

Several of the measures in this index were present in the prior version of the Innovation Index, but version 2.0 is greatly enhanced by including measures for industry performance and expanding the sophistication of the Patents Core Index.

Job Growth to Population Growth Ratio

Measure: The Ratio of Job Growth to Population Growth measures whether employment is growing more or less quickly than the general population, from 2002 to the latest year available.

Rationale: Historically, employment growth has been an important measure in academic and policy research. Indeed, employment growth has been used to measure economic growth and as an output of innovation. Indeed, Atkinson and Stewart (2012) argue that innovation leads to job growth in three ways: expanding new products and services, increasing employment and productivity, and leading to increased wages and lowered prices. A measure of job growth was used in one form or another in other innovation indexes. Empirical research has found that university R&D, new firm formation, favorable industry mix, human capital and entrepreneurship lead to employment growth, which in turn affects income and subsequent economic growth.

However, employment growth is highly dependent on population growth. Population growth is a strong and positive predictor of employment growth, and differences in employment growth between countries or regions is often attributable to differences in population growth.[4] Moreover, several articles point out that the differences between employment data from surveys are due to variations in the estimation of the population control. Previous work looking at employment growth either compares it to population growth or includes it directly in their models. Acs and Armington (2004) look at the employment rate relative to the population growth rate in order to compare regions more effectively. For this index, we use the ratio between employment growth and population growth. High employment growth relative to population growth suggests jobs are being created faster than people are moving to a region.

Even though the ratio measures the change in level between jobs and population and, therefore, can't be used to compare rates of growth, it can rank order counties or regions in terms of employment performance. A high ratio between these two variables indicates strong employment growth. This ratio can vary dramatically county to county. A negative value signifies that population is growing while employment is declining or vice versa. In cases for which population is declining while employment is increasing, the absolute value of the ratio is used as that would be considered favorable employment performance. The conditional nature of the equation provides for the fact that a county or region may have growing employment but a declining population, which would be considered a positive outcome.

References are available on page 79 and the equation on page 116.

Change in Share of High-Tech Industry Employment

Measure: Change in Share of High-Tech Industry Employment measures the degree to which the region's high-tech industry jobs are growing or declining in concentration or importance. It compares the share of high-tech employment from 2002 to the share of the latest year available.

Rationale: Just as the share of high-tech employment in a county is an important input, the extent to which that share is increasing relative to total employment is an important performance measure. In a similar way, this measure also registers the degree to which home-grown, high-tech firms have expanded their presence. Growth in the share of high-tech employment suggests the increasing presence of innovative activity

[4] There is still, however, some debate as to whether population increases lead to more jobs to keep up with the demand or if an increase in employment opportunities leads to more immigration.

and signifies that high-tech firms are growing in the region—both in relative and absolute terms.

References are available on page 80 and the equation on page 117.

Industry Performance

Measures

- Cluster Diversity is a "place your eggs in many baskets" measure that quantifies whether a region is relatively concentrated in just a few industries or whether the region has a broad assortment of industries. The evenness of a region's industrial employment mix is compared against a national value of industry diversity.
- Cluster Strength is the flip side of the cluster diversity measure. It measures the degree to which clusters may dominate the employment in the region. It has been argued that clusters grow more quickly and are more resilient to economic shocks.
- Cluster Growth Factor measures the percent of employment growth in a region—even a region that is losing jobs—that can be attributed to strong clusters. A regional growth cluster (RGC) is defined as having growing employment, being a significant and increasing share of the regional economy. This measure can be interpreted as the percent of total employment that can be attributed to the regional growth clusters. The greater the percentage, the greater the role that RGCs had in job growth.

Rational: Industry clusters are agglomerations of closely related industries. Porter (2000) maintains that the co-location of companies, customers, suppliers and other institutions create an environment of increased rivalry that leads to higher pressure to innovate. Industry clusters are also important for innovation because they facilitate the growth of startup firms, which are considered key agents of innovation. In comparison to more mature firms, startups may be more likely to identify new technologies and new market opportunities.

Some argue clusters might decrease incentives for new business formation due to increased competition and crowding-out effects (or congestion costs) that result in diminishing marginal returns to entrepreneurial opportunities. Others claim clusters might lower the cost of starting a business by providing specialized suppliers, a local customer base, and producers of complementary products and services. Delgado et al. (2010) conducted an empirical analysis to inform this debate and conclude that, while there is evidence of negative crowding-out effects on entrepreneurship, the cluster environment that surrounds an industry expands the pool of available resources and reduces the cost of starting a new business.

Industry specialization is measured by the share of regional employment in the industry as compared to the share of U.S. total employment in the national industry. Similarly, cluster specialization is measured by the share of regional employment within the cluster (outside the industry) as compared to the share of U.S. total employment in the national cluster (outside the industry). For example, let *i* be the medicinal and botanical manufacturing industry within the biopharmaceuticals cluster. Then, biopharmaceuticals specialization would be measured by the share of regional employment belonging to the other industries within the biopharmaceutical cluster (excluding the employment from the medicinal and botanical manufacturing industry) as compared to the share of U.S. total employment in the national biopharmaceutical clusters (outside the medicinal and botanical industry).

High regional industrial specialization is a successful strategy for regional economic growth as long as the primary industry or cluster in a given county or region is growing. If the key sectors of a region see their competitive position threatened, that region will become vulnerable to the struggles of these industries. Dependence on a particular industry cluster implies vulnerability to the economic gains and losses of that cluster. In order to limit the vulnerability to the "ups and downs" of a key regional cluster, policymakers often advocate a strategy of regional industrial diversification.

Industrial diversification provides a more stable economic outlook for regional economies since they are less dependent on a single industry. A recent study evaluated the role of economic diversification for Appalachian counties traditionally specialized in manufacturing, mining and forestry. The University of Illinois researchers concluded that a viable diversification strategy should not simply be to "encourage the emergence and expansion of a generically diverse mix of economic activity, but rather to support the competitiveness and growth of a number of specializations or clusters that can serve as the multi-legged foundation for the local economy" (Feser et al., 2014, p. vi).

It is important to note that diversification does not necessarily imply higher incomes or faster growth. An economy might be considered diverse because, for example, a large manufacturing plant recently closed, thereby decreasing the regional level of specialization. Successful diversification will promote several areas of specialization in such a way that the decline in one sector can be offset by the growth in another sector.

This bundle of measures attempts to strike a balance between the economies of agglomeration (clusters), the benefits of diversity of industries and the sources of employment growth in a region.

References are available on page 80 and equations on page 117.

Gross Domestic Product (GDP)

Measures

- Gross Domestic Product per Worker measures economic output per worker for a single year by dividing a region's current-dollar GDP by the region's number of employees for the latest year available. GDP per worker can be a measure of economic performance because it includes both compensation to labor and returns to capital.
- Change in GDP per Worker measures the increase (or decrease) in current-dollar GDP per employee from 2002 to the latest year available.

Rationale: Carried over from the Innovation Index version 1.0, GDP per worker is a measure of productivity. Innovative products or processes would not be undertaken if the action would not increase wages or profits. As the single most important measure of productivity available—GDP per worker—this core index incorporates both the current level of a county's economic success and also measures growth in worker productivity.

References are available on page 81 and equations on page 122 .

Patents

Measures

- Change in (Average) Patenting Rate compares the three-year average of patents per 1,000 workers at the beginning of a 10-year time frame to the most recent three-year average number of patents in the region.
- Patent Diversity measures the mix of a region's patent activity by comparing the diversity of patent making in the region against the U.S. patent diversity score for the latest three years of available data. If the score is above 1.00, the region is more diverse than the U.S. as a whole.
- Patents by Institution Type reports the number of patents for five institution types, from individuals to companies to government. Note that because this measure is descriptive, it is not included in the index calculation, but is simply presented for informational purposes.

Rationale: As discussed in the knowledge creation and diffusion section, patents are critical for measuring regional innovation as they represent current innovation and predict future developments. While other indexes and Innovation Index version 1.0 have used a measure of the number of patents, version 2.0 includes a measure of the change in the number of patents in a region over a 10-year period. This measure captures the trends in innovation activity in a region.

The variety, or type, of patents within a region are also important. On the one hand, a diverse set of patent technologies might be useful for a region in order to adapt to future changes in businesses' needs. On the other hand, specialization within a region has been found to increase economic development if that technology is needed elsewhere. Creating patents within a diverse set of technologies shows the ability and/or willingness of the region to adapt to changes in the economy, while focusing on one type of technology might show the region's ability and/or willingness to specialize and fill a particular niche in the world economy.

Previous research has found that the complexity of the patent knowledge affects how widely it spreads. However, the mechanism through which patents lead to innovation is through the inventors and their networks. Indeed, patents lead to economic growth and spread to neighboring regions because knowledge related to patents is shared across interpersonal ties. It is, therefore, important to look at what kind of institutions (federal government, non-government organization, individuals or foreigners) filed the patent in order to understand how the knowledge surrounding the patent might spread and lead to subsequent innovation. We, therefore, also include a descriptive measure (not included in the overall index calculation) for the total number of patents per institution type.

Patent data are coded to distinguish between the residence of the filer and the recorded location of the employer (if the applicant is not a private inventor), but the recorded location of the employer may or may not correspond to the location of the work that produced the patent, especially if the employer is a large, diversified company with many locations. In addition, the available patent data do not cover the universe of all patent types. Patent data are recoded from the raw data provided by the U.S. Patent Office and awards patents to any county from which one of the filers reported as their location. This means that for any single patent with more than one filer, a patent may be counted multiple times if filers are located in different counties.

Only utility patents are used in these measures. Utility patents are items intended to serve a function, in contrast to design patents, which are nonfunctional in nature and include such things as new computer fonts. Recalled patents and statutory invention patents are also excluded. Be aware that patents can be an inaccurate indicator of innovation outcomes, particularly in areas where a single firm overwhelms the total patent count, such as Eli Lilly, the pharmaceutical giant headquartered in Indianapolis.

References are available on page 81 and equations on page 122.

Economic Well-Being Index

Innovative economies improve economic well-being because residents earn more and have a higher standard of living. Decreasing poverty rates, increasing employment, in-migration of new residents, and improvements in personal income signal a more desirable location to live and point to an increase in economic well-being.

Most of these measures were present in version 1.0 of the Innovation Index, but this new version does include two additional measures: income inequality and a dependency ratio based on income sources.

Per Capita Personal Income Growth

Measure: Per Capita Personal Income Growth is calculated by the average annual rate of change from 2002 to the latest year available.

Rationale: As an alternative to measuring remuneration based on place of work, per capita personal income (PCPI) measures income by place of residence. Personal income is the broadest measure of a person's income because it includes rental income, dividends and interest payments, in addition to salary, wages and benefits. As a result, it is probably the best measure of well-being. On the other hand, the measure is based on the location of residence, not the location of work. Thus, high personal income may or may not reflect the economic returns to innovation within a county or region with a large number of people who commute to work.

References are available on page 82 and the equation on page 124.

Compensation

Measures:

- Annual Wage and Salary Earnings per Worker Growth is calculated as the average annual rate of change in wage and salary earnings per worker from 2002 to the latest year available.
- Change in Proprietor's Income per Proprietor is calculated as the average annual rate of change in proprietors' income per proprietor from 2002 to the latest year available.

Rationale: In contrast to personal income reported by the U.S. Bureau of Economic Analysis (BEA), compensation data convey how much workers make based on their place of work. Likewise, proprietors' income is also based on place of work. This core index, therefore, provides an arguably stronger relationship between the activities of innovation and the rewards of innovation based on where innovative activities occurred.

References are available on page 82 and equations on page 124.

Income Inequality–Mean to Median Ratio

Measure: This Income Inequality measure, in contrast to the Gini coefficient that is used in the Social Capital Index, is calculated by comparing the region's mean household income with the region's median household income. It shows how income is skewed. The inverse is used because high inequality is considered a negative outcome; thus, higher values denote more equality between the poorest and the richest residents. Smaller values denote that the income distribution is less equal.

Rationale: Income inequality, it is theorized, affects economic development and growth. On the other hand, economic growth may influence income inequality. Regarding income inequality and economic efficiency, economists of different stripes have claimed a positive, an inverse, as well as a non-linear relationship. Theoretical arguments posit that unequal income distribution impacts growth positively by providing incentives to work, save and invest. Others suggest negative effects on human capital development, health, political and social stability, consumption of goods and services, the supply of public goods, lower R&D investment, entrepreneurship, and economic development more generally. A growing consensus supports the conclusion that income inequality is likely inversely related to economic growth—that is, higher levels of inequality negatively affect economic growth.

Recent research offers compelling counterevidence to the idea that there is a tradeoff between equality and efficiency, defined as the highest level of production given available resources. Researchers find that the tradeoff between equality and efficiency may not exist in the medium or long run. In fact, it appears that greater equality promotes sustainable medium- and long-term growth.

Given that income inequality is considered a negative outcome, this measure is one of four that are inverted. Thus, a higher index score reflects greater income equality.

References are available on page 82 and the equation on page 125.

Average Poverty Rate

Measure: The inverse of the Average Poverty Rate is simply the number of a region's population that live below a threshold level of income, averaged over the last three years of available data. The inverse of the poverty rate is used because a high poverty rate is a negative outcome.

Rationale: Innovative economies have greater employment opportunities with higher compensation, thus lowering rates of poverty. Reduced poverty rates will tend to lag growth in employment opportunities. As a result, the last three years of the most recent data are used.

Given that high poverty is a negative outcome, this measure is one of four that are inverted. Thus, a higher index score reflects lower poverty rates.

References are available on page 83 and the equation on page 125.

Average Unemployment Rate

Measure: The inverse of the Average Unemployment Rate is a three-year average of the number of unemployed in a region divided by the three-year average of the labor force, using the latest three years available. The inverse is used because high unemployment is considered a negative outcome. Unemployment is also sensitive to economic bust and boom cycles and, for that reason, the change in unemployment is not reported.

Rationale: The unemployment rate is the number of people seeking employment as a percentage of the total labor force. Areas with high levels of innovation are expected to have low unemployment rates.

Given that unemployment is a negative outcome, this measure is one of four that are inverted. Thus, a higher index score reflects lower unemployment rates.

References are available on page 83 and the equation on page 126.

Dependency Ratio–Measured by Income Sources

Measure: The Dependency Ratio represents the degree to which a region relies on government income programs. The region's ratio is calculated by summing personal transfer receipts—Social Security, disability and welfare payments, for example—and dividing by the sum of personal income totals.

Rationale: Opponents of government social spending argue that transfer payments provide a disincentive to employment and investment, while supporters point out the poor's tendency to spend rather than save—suggesting that transfer payments actually work to stimulate the economy. The literature on the relationship between social expenditures and economic performance identifies a number of plausible mechanisms through which government transfers may affect productivity and economic growth—namely, via savings, fertility, human capital, inequality and longevity. The inconsistency of the corresponding empirical work and economic theory, however, makes it difficult to determine whether transfer payments have a positive or negative effect on economic performance or innovation.

Research that considers the relationship between economic performance and specific types of government transfers suggests that actuarially fair pay-as-you-go pension systems promote economic growth and lessen income inequality. It is also said that social protection, in the form of employment and unemployment benefits, may help to correct for failures in the market related to skill formation. Specifically, Estevez-Abe et al. (2001) argue that workers will only invest in industry- and firm-specific skills if they can rely on unemployment and employment protection, respectively. Innovation-leading firms and industries may be the primary beneficiaries in this case, given their reliance on specialized rather than general knowledge, skills and training.

In sum, there are divergent theories and mixed empirical findings about the benefits, costs and efficacy of government income support programs. Given that the motivation to innovate is to capture the rewards from innovation in terms of greater income—with the acknowledgement that innovation by social entrepreneurs is not usually financially driven—it is reasonable to hypothesize that high dependence negatively affects a region's innovative activities.

Dependency on income that is not work-generated is not considered an indicator of innovative activity. As a result, this measure is one of four that are inverted. Thus, a higher index score reflects lower dependency rates.

References are available on page 84 and the equation on page 126.

Average Net Migration

Measure: Average Net Migration is the average net domestic migration rate from 2009 to the latest year available.

Rationale: Average net migration measures the extent to which a county or region is broadly appealing and excludes other elements of population dynamics (such as births). While people may migrate into a region for a host of reasons, from employment opportunities to environmental amenities, migration out of a region almost certainly signals declining economic conditions and the inability to keep the innovative talent that will spawn economic growth in the future.

Migration of people, especially working-age adults, serves as an indicator of whether an area is attractive to job seekers and families. Low unemployment rates and opportunities for higher income are among the most common and powerful reasons for migration within this demographic.

References are available on page 84 and the equation on page 126.

State Context

The State Context category is not included in the calculation of the overall index since data are not available at the county level. Nevertheless, since measures in this section are important to understanding the innovative environment, the web tool provides these data at the state level for users to explore. This category has been greatly expanded since version 1.0. Except for science and engineering graduates and R&D spending by universities and private firms, all of the measures are new to version 2.0 of the Innovation Index.

Per Pupil Education Spending in K-12

Measure: Education Spending per Pupil is taken directly from the National KIDS Count data set and adjusted for regional cost differences using the National Center for Education Statistics Geographic Cost of Education Index.

Rationale: Per pupil education spending in K-12 gives an indication of a state's level of commitment to education. Primary and secondary education provides basic knowledge and skills that help individuals pursue and succeed in higher education, research and employment in innovation-related fields.

The Global Innovation Index recognizes that education is an integral part of innovation and that access to basic and vocational education is central to human capital development. K-12 education provides basic knowledge and sometimes technical skills that enable students to move onto higher levels of education that support innovation activities more directly. A large body of literature investigates the role of education expenditures in predicting student performance, which has implications for economic performance. The results of individual studies are mixed. Coulson (2014), for instance, examines U.S. data on state-average SAT scores and education spending over the last 40 years and finds no correlation between expenditures and student academic performance. However, recent meta-analyses conclude that, on average, higher levels of education expenditures are associated with better standardized test scores and lower dropout rates. Schooling resources, including smaller class sizes and teacher salaries, are shown to be positively associated with student outcomes. Aos and Pennucci (2012) find that the effect of education spending on student performance is stronger in lower grades.

Education expenditures serve as a reasonable proxy for how much a state prioritizes education and human capital development. Giving relatively high priority to education conceivably has positive implications for state-level innovation. Given that test scores reflect ability and graduating high school is a precursor to tertiary education, it is also reasonable to conclude that greater K-12 education funding, if spent wisely, will increase the quality of human capital and the proportion of the population with tertiary educational attainment. Human capital, of course, is one of the primary drivers of innovation capacity.

References are available on page 84 and the equation on page 127.

Science and Engineering Graduates from State Institutions

Measure: Science and Engineering Graduates from State Institutions—both bachelor's and advanced degrees—is calculated using the number of graduates from state institutions divided by the state population in thousands.

Rationale: The number of graduates from science and engineering programs within a given state increases the supply of individuals trained to meet the growing demands on the skilled labor force.

References are available on page 85 and the equation on page 127.

STEM Talent Flow

Measure: STEM Talent Flow captures the number of incoming migrant STEM workers as a proportion of the working-age population (measured in thousands), defined as the population between the ages of 18 and 66.

Rationale: An influx of STEM workers has positive implications for human capital and innovation in the receiving state. STEM workers are in a better position to utilize existing innovations and to create new ones. Workers who possess STEM skills are highly sought after by innovative firms. Workers in STEM occupations drive innovation, productivity and competitiveness. STEM workers also contribute to the stability of the economy and have a role in sustaining economic growth. States that gain workers in STEM occupations may, therefore, stand to benefit from more optimal levels of innovation and economic growth.

In-migration can raise human capital levels and support technological progress within the receiving state. Given that STEM workers earn, on average, 26 percent more than non-STEM workers, STEM migrants may also increase consumption, living standards and income over the long term. Research shows that advanced education in STEM fields is correlated with high rates of entrepreneurship and innovation. Thus, STEM in-migrants who have this advanced educational background may increase entrepreneurship and innovation within the state.

The in-migration of workers in STEM occupations is also particularly beneficial for firm-level innovation capacity, determined in part by the availability and quality of human capital. The 2014 Brookings report, "Still Searching: Job Vacancies and STEM Skills," unearths the relative shortage of STEM workers at all skill levels in the United States, finding that, on average, job vacancies requiring STEM skills take twice as long as non-STEM jobs to be filled. The in-migration of STEM workers can help offset this imbalance between supply and demand in the labor market. STEM in-migrants provide employers in innovation-related fields the human resources needed to increase firm competitiveness and the availability of goods and services.

In sum, STEM in-migrants offer states and the STEM employers within them many potential benefits associated with innovation, including human capital and productivity gains, an increase in the demand for the products of innovation, additional revenue, and higher rates of entrepreneurship.

References are available on page 85 and the equation on page 127.

Research and Development

New knowledge comes with new possibilities for innovative products and services. R&D spending data from the National Science Foundation (NSF) is one of the classic measures for assessing the capacity for developing knowledge.

Measures:

- Total R&D Expenditures as a Percentage of GDP is a simple ratio of total R&D spending in the state from NSF divided by the state's current-dollar GDP (from BEA) and averaged across the last three years available.
- R&D Spending by Universities and Private Firms Per Capita is calculated using the NSF data on spending by institution type divided by total state population and averaged across the last three years available.
- Industry-Performed R&D as a Percentage of Industry Output is calculated using spending data by industry and dividing by total industry output, both as defined and directly reported by NSF, and averaged across the last three years available.
- Federal Expenditures for Academic and Nonprofit R&D Per Capita includes funds disbursed by all the federal agencies in a year for R&D in universities, colleges and nonprofit organizations. The NSF spending data are scaled to the state population and then averaged across the last three years available.
- University R&D Expenditures in Science and Engineering Per Capita is calculated using the science and engineering R&D spending by universities (as reported by NSF) divided by the state population and then averaged across the last three years available.
- Industry Funding of Academic Research Per Capita measures all university expenditures that were financed by businesses. The NSF spending data are scaled to the state population and then averaged across the last three years available.
- State Funding of Academic Research Per Capita includes all university expenditures that were financed by either the state or local governments. The values are scaled to the state population and then averaged across the last three years available.

Rationale: R&D spending is often used to predict innovation and economic growth, and recent indexes have included R&D spending to measure innovation. Audretsch and Feldman (1996) find that both industry and university R&D positively affect the Gini coefficient of innovation and production in the state. Moreover, looking at R&D spending as part of a financial resource factor, Hall (2007) finds that this factor significantly increases the number of Small Business Innovation Research awards in the state and gross state product per person. Research in Europe shows that holding other important regional predictors constant, not only do total R&D expenditures directly lead to more economic growth, but regions with low R&D expenditures are unable to take advantage of technologies developed in other regions. However, to measure innovation, it is important to look beyond total R&D spending and also include measures of both the source of funding and the performer of R&D.

In order to take into account the variety of effects R&D can have on innovation, we include measures to account for the different performers of R&D. Industry R&D expenditures reflect business involvement in creating new knowledge, which leads to more economic growth in the region. Industry R&D is positively and significantly related to the Gini coefficient of production and of innovation in the state. In Europe, industry R&D predicts patenting and productivity levels, even in neighboring regions.

On the other hand, because of their less-competitive nature, academic and nonprofit R&D not only leads to award-winning innovation, but can also spread easily across institutions and regions. Within states, university R&D has been found to predict corporate patents, Gini innovation and production, and new plant formations. At a more local level, academic R&D positively affects new firm formations, industry R&D and other measures of innovation and economic development.

Finally, since academic research relies heavily on external funding, the source might impact how successful university R&D is at fostering more innovation. First, if states and businesses fund academic R&D, it reflects a larger R&D strategy and is, therefore, a sign that the region welcomes efforts toward knowledge creation. Second, universities sometimes develop and increase their R&D outputs in order to get greater sources of funding. Finally, a variety of funding can lead to greater and broader research implications, both in academia and in industry. Indeed, federal and industry support of academic R&D has been found to lead to more patenting. In Norway, Gulbrandsen and Smeby (2005) find a significant relationship between industry funding and the quality and quantity of university research. Therefore, high levels of federal and industry funding of academic research leads to greater knowledge creation and more opportunities for innovation. Since we are looking at state effects for regional growth, state (and local) government funding of academic research is also included.

References are available on page 86 and equations on page 128.

Institutionally-Based Startups

Measure: Institutionally-Based Startups are the number of entities that universities and other nonprofit research institutions formed and headquartered in the home state scaled by total R&D expenditures reported by those institutions. Note: These are not NSF R&D data.

Rationale: Startups license technology produced by universities and other research institutions to create new and improved products, services and processes. High in-state startup rates relative to institution R&D implies efficient technology transfer and signifies concentrated innovation activity.

Technology transfer is an inherently innovative activity, representing the transformation of new knowledge into economic, or commercializable, knowledge. One way technology transfer contributes to economic growth is by encouraging the creation of new firms and employment (e.g., startups formed on the basis of licensed technology). Nascent startups are reportedly one of the most important factors linking entrepreneurship to economic growth. Successful startups improve competition and have the effect of increasing productivity, thereby promoting economic growth. Acs and Plummer (2005) find that new startups contribute more knowledge to economic growth than incumbent firms. There is also evidence that startups produce more of the major innovations in less-crowded technological areas, and that small startup firms are better connected to regional knowledge networks than larger firms.

Growing acceptance of endogenous growth theory, which emphasizes the role of knowledge in generating economic growth, has spurred a great deal of research on the nexus between entrepreneurship and economic performance. Corresponding empirical studies commonly employ startup rates and related rates (e.g., number of jobs created by startups) to gauge technology transfer and, more broadly, entrepreneurial activity. Efforts have been made to extend endogenous growth theory to incorporate entrepreneurship more explicitly into economic growth models. Most notably, the knowledge spillover theory of entrepreneurship posits that startups act as a conduit, contributing to economic growth by facilitating the spillover of knowledge from knowledge creators to new firms. Audretsch and Lehmann (2005) show that the theory of knowledge spillover entrepreneurship holds for regions as well as industries. Specifically, they find that the number of young and high-tech firms is greater in regions with high knowledge capacity and high university knowledge output.

References are available on page 87 and the equation on page 131.

Small Business Innovation Research and Technology Transfer Awards

Measure: Small Business Innovation Research and Small Business Technology Transfer grant dollars are summed from 2002 to the last year of available data and divided by the state population. A long time series is used because this type of grant funding is for early stages of business development, is relatively small and can fluctuate considerably over time.

Rationale: Various federal agencies have a slice of their budgets devoted to innovative research and technology transfer in the non-government sector. The intent is to help commercialize science in the marketplace. This measure seeks to quantify the degree of investment in early-stage, high-risk ideas.

The U.S. government subsidizes commercial research and development due to the belief that profit-maximizing firms underinvest in R&D. The economic justification is that social returns to private R&D are often higher than private return; thus, some research projects would benefit society yet be privately unprofitable. A subsidy would lower the cost to the firm and subsequently make it privately profitable as well. Two subsidized R&D programs are Small Business Innovation Research (SBIR) and Small Business Technology Transfer (STTR) grants. SBIR and STTR grants are investments in the early stages in the development process—a high-risk phase.

The SBIR program, administered by the Small Business Administration (SBA), is reputed to be the largest seed capital fund for development of new products and processes in the world. It provides competitive grants to entrepreneurs seeking to conduct proof-of-concept research (Phase I in SBA terminology) and prototype development (Phase II). The STTR program makes competitive awards to small business and public sector partners to promote technology transfer activities. SBIR and STTR grant awards to businesses are, thus, an indicator of activity in the early stages of the process of converting ideas into commercial innovations.

Research has shown that SBIR/STTR grants tend to be clustered in larger cities, which intuitively makes sense due to the localities having more resources, as well as more economic activity. Therefore, instead of measuring SBIR/STTR grants by establishment sizes, we created a per capita SBIR/STTR measure.

References are available on page 88 and the equation on page 131.

Kauffman Entrepreneurship Index

Measure: The Kauffman Index of Entrepreneurial Activity measures the percentage of people ages 20 to 64 who do not own a business in the first survey month that start a business in the following survey month. The survey-based data are taken directly from the Kauffman Foundation. The index estimates new business creation, defined as the percentage of adult non-business owners who start a business.

Rationale: The Kauffman Index of Entrepreneurial Activity captures the new business creation aspect of entrepreneurship and is used in a number of studies on entrepreneurship. Hafer (2013) finds that entrepreneurial activity as measured by the Kauffman Index is associated with higher state economic success (e.g., state output, income and employment). However, other studies report that the Kauffman Index state rankings are less intuitive than rankings generated from other indexes of entrepreneurship, and that the Kauffman Index can be less relevant than other measures of entrepreneurship depending on the relationship being examined. The results of Weber and Powell's (2013) study show no significant relationship between economic freedom and entrepreneurship as defined by the Kauffman Index.

Still, there are advantages to including this measure of entrepreneurship. One advantage of using the Kauffman Index over other measures of entrepreneurship is that it represents the flow, not stock, of entrepreneurial activity. Rather than capturing both new and old business activity, it includes only new business ventures. Another benefit is that it uses Current Population Survey (CPS) data instead of payroll records or business incorporation data, which are thought to underestimate entrepreneurial activity. The use of payroll data likely leads to an underestimation of entrepreneurial activity, given that new firm startups often have few, if any, employees. This is an important consideration if one wants to capture new entrepreneurship in technology areas.

Although the Kauffman Index does not take into account businesses that fail after the first month, it does indicate the public's level of interest in business ownership, which is shaped by various economic, political and environmental factors that can work to promote or discourage entrepreneurial activity.

References are available on page 88 and the equation on page 132.

Business Formation and Survival

Measures:

- Establishment Entry Rate is a three-year average of the number of new establishments that are less than one year old divided by the total number of active establishments.
- Establishment Survival Rate is a three-year average of number of establishments born in one year that still exist the following year divided by the total number of establishments.

Rationale: New business formation spurs competition, enhances productivity, adds jobs and promotes long-term economic growth. Higher rates of establishment openings signify greater startup activity, while establishment survival rates indicate the relative risk associated with creating a new business in a particular area, as well as how the economy affects firms at various stages in their development.

The importance of business dynamism to employment, productivity and sustained economic growth is virtually undisputed—and perhaps the most critical aspect of this process is the creation of new firms. New firms spur and strengthen competition among businesses, increasing productivity and economic growth over the long term. Startups are also instrumental in bringing about new, often game-changing innovations that open up new markets and disrupt the status quo. It is often said that new business creation increases employment; however, as Fritsch (2008) correctly notes, the employment effects of business formation are not always positive. Entrants, in addition to creating new jobs, also pressure incumbent firms to exit and scale down operations, resulting in a loss of jobs—and potentially a net loss in jobs.

Low-productivity regions with few quality entrants, scarce resources and underdeveloped innovation systems are less likely to experience positive employment effects from business formation. Empirical research confirms that the effect of new business formation on employment varies considerably across regions, with the effect more pronounced in high-density, high-innovation areas.

Following Fritsch and Schroeter (2011), we measure business formation as the rate of new establishments (defined as the number of establishments less than one-year old) as a share of total establishments. Higher rates signify greater startup activity. We also include a measure of establishment survival, specifically the percentage of new establishments that remain in operation one year following their birth. Survival rates provide an indication of the relative risk associated with starting a new business in an area and how the economy affects firms at different stages of their development.

Faberman's (2011) work shows that high-growth metropolitan areas have higher rates of establishment entry than low-growth metropolitan areas, but that their entrants are less likely to survive than entrants in low-growth metropolitan areas. Taking into account establishment age, the combined effect of entry, exit and growth of establishments aged five years or less accounts for approximately 61 percent of the variation in employment growth at the metropolitan level, despite these establishments making up only 23 percent of all establishments.

References are available on page 88 and equations on page 132.

Volunteer Rate

Measure: The Volunteer Rate is the number of residents in a state who report having volunteered divided by the state population, and then averaged over three years. While this measure would be better included as part of the Social Capital Index, it is available only at the state level, so as a result, it is placed under State Context.

Rationale: Civic engagement through organizational memberships can be a strong measure of social capital and, beyond mere membership, such measures could incorporate the level of activity from passive membership to leadership roles. Given that social capital can be defined by the ability of a community to solve its own problems and marshal its own resources, volunteering is an appropriate measure because it is signaling that a community is responding to needs, and individuals are collaborating with each other toward a common goal. Adeponu (2013) developed an index measure of community commitment that included elements for how one participated in volunteer activities along a spectrum—from simply attending an event, to attending multiple events, to taking a leadership role by organizing an event.

References are available on page 89 and the equation on page 133.

Interpreting the Index

Interpreting the Innovation Index is not as simple as an initial glance may suggest. The index ranks a region's performance relative to the United States and other regions on a continuous scale. Additionally, the Innovation Index has no teleology, no simple, single goal. "Economic development" may be one obvious goal, but can be further conceptualized as increasing GDP, or household income, or full employment, or income equality, or expanding personal autonomy. There is no single dependent variable.

The index is a collection of measures baked into one at-a-glance number, not unlike the leading economic index of the Conference Board[5] (except the components have a more equal weighting). The headline index is an aggregation of many disparate parts that may or may not move in tandem with each other.

The Innovation Index is an aggregation of underlying major categorical indexes for innovation inputs and outputs. If one were interested in finding out how the volume of inputs affects the quantity of outputs, he would not combine them into one measure. From the perspective of a person modeling the factors that contribute to economic growth, she would not mingle inputs and outputs because she would not be able to answer the question of what combination of inputs generates the better outputs. That said, in the admittedly simple framework of this index, combining inputs and outputs is not such a bad strategy. The higher-scoring regions will tend to exhibit high levels of both inputs and outputs, whereas the lowest-scoring regions will have low levels of inputs and outputs. The murky analytical area is for regions that may have a high overall score but only due to a relative advantage in either inputs or outputs, but not both simultaneously. The question then becomes "why?" And it is here that the interesting analytical work will be done to determine why, for example, a region has particularly high GDP per worker when it has relatively low educational attainment. It may be that the region is enjoying a natural resource boom that is driving economic growth.

While the target market for the Innovation Index 2.0 is economic development practitioners, the measures and data collected, processed and presented in the index are of great value to researchers and analysts who want to explore the nature of the

[5] See www.conference-board.org/economics/indicators.cfm.

relationship between innovation capacity—the innovation inputs—and the desirable outputs incumbent upon innovation. It is expected that researchers will depart from the equal weighting scheme as they assess the influence of different drivers according to empirical relationships. The IBRC research team would welcome efforts to derive an empirically based index. Such an index would identify those specific factors with the greatest influence on economic growth, while controlling for some non-innovation factors, such as resource dependency or industrial legacy. Understanding which factors exert the greatest influence on economic growth would not only assist policymakers, but help practitioners as well.

The research team had to answer a critical question as we developed Innovation Index 2.0—Which is more important: a simple index calculation or a more comprehensive set of innovation measures? The research team chose the latter. As a result, the index values or scores are not derived in the same manner as with the first innovation index. In the first iteration, the indexes were constructed in a very straight-forward manner using the value for the nation as the benchmark "100" value. In short, the values for a particular measure were divided by the national value.

The Innovation Index 2.0 expanded the set of measures enormously. Many practitioners, policymakers and analysts will be thrilled to see measures for foreign direct investment and knowledge spillovers. The downside to a more comprehensive set of measures is that there are many empty cells (lots of zeros) and also many cases of wildly large outliers. If the simple index calculation described above were used, some index values would top 14,000, for example, venture capital in the Bay Area. In order to make regional comparisons viable at all, we used a method to scale the data in a fashion that maintained the rankings between regions using a continuous scale. For those measures for which the data have extreme outliers or many zeros (e.g., over 2,500 counties have zeros values for venture capital), the U.S. benchmark index value deviates from 100, sometimes significantly.

The method we used was to transform every variable to a normal distribution (see the "Index Calculation" section on page 13 for more details).

These procedures maintain rank ordering for any particular year and keep the extreme cases within range. This does not allow for consistent year-over-year changes in the index for a particular geographic definition. Intra-temporal comparisons (i.e., comparisons within the same year) between the same regional units of analysis (i.e., counties, metros, economic development districts) are still valid. It is *invalid* to compare a county unit of analysis with an MSA, for example, as they are two different geographic units of analysis. Performance, or progress toward a goal, can be measured over time using changes in the individual measures for a particular geographic unit.

One may question the wisdom of creating an index where the benchmark value is not 100. Fair enough. But consider this: For one of the best behaved data series used in the index, bachelor's degree attainment, only 483 counties (out of 3,110) would have an index value above 100. In short, that magical 100 benchmark, or national average, does not reflect a vast proportion of the nation. The middle index value among all the counties in the nation is 67. For this reason, there was little to be gained by maintaining the 100 national benchmark as an inviolable rule. In order for a user to discern how a region is doing, the website provides the national benchmark, the median of all geographies and ranks for each measure.

Regional Performance Goals: Gauging Innovation over Time

The Innovation Index 2.0 index values are not suited to measure changes in innovation capacity or outcomes over time. From one year to the next, index values may change because a region's concentration of STEM occupations increased—a genuine increase in innovative capacity—or they may change because the normal distribution transformation can change in the index score, even while maintaining the relative rank of one region compared to another. Thus, the innovation scores are for comparing peer regions in one time period.

Economic development practitioners and local regional analysts would not find this very satisfying, however. Often, they wish to measure progress toward some goal or some outcome over time to see how they are doing. After all, isn't one purpose of the index to help a region assess its strengths and weaknesses and then craft a strategy and pursue goals based on that strategy? Many users need to chart progress over time.

To this end, the final version of the web tool will provide raw (that is, not indexed) metrics for the majority of the measures. (Some raw data are proprietary and cannot be disclosed.) In this way, one can identify trends across a wide array of index components, for example, educational attainment, business formation, proprietorship, STEM occupation density, and the like. To the extent possible, the web tools will provide five years of data for each measure in order to assess trends. These data will also be downloadable for the user to create additional graphs and visualizations.

Conclusion

The Innovation Index is a web-based tool for regional economic development practitioners to identify the knowledge-based and innovation-based strengths and weaknesses of a regional economy. Many of the measures used for the index gauge the foundational elements that are currently in place in the region for future, innovation-driven economic growth. Some of the measures gauge the degree to which the region is attractive to new talent and firms that may also enhance the regional economy, but those same measures of attractiveness are also measures for retaining current talent and firms.

Certain regional characteristics, in other words, work like gravity, keeping objects on the ground and pulling objects to the ground. It is hoped, therefore, that the Innovation Index is not primarily used to try to attract outside firms, resources and talent, but is primarily used to identify indigenous sources of innovation and ways to fortify those sources. Encouraging homegrown entrepreneurs with personal commitments to the region, for example, is preferred to attracting talent with minimal personal investment in the region.

Developing the second iteration of the Innovation Index greatly expanded the scope of the theoretical and empirical literature used to define and refine the innovation measures and significantly expanded the data sources used to calculate the index. Version 2.0 became a lot more comprehensive and a lot more complicated. The data and methods pursued by the research team for designing and building an upgraded index were in tension. The aim was to appeal to two audiences: both academic and policy-related researchers, as well as economic development practitioners in the field. The research team hopes that it found the “sweet spot” of complexity of construction and simplicity of use. The research team elected to provide as much data as possible to enable practitioners to learn more details about their region. For example, expansion stage venture capital is a function of total venture capital, and only one of the two variables would likely make it into a statistical model, but practitioners were interested in knowing more detail. The research team hopes it has done well by them.

The version 2.0 index is a follow-up to creating a comprehensive innovation measure at the county-level unit of analysis in the United States. Using county-level data allows users to define their region as they wish and it allows researchers the ability to compare regional performance over time using consistent geographical definitions. For example, MSA definitions change over time, but building regions by county permits consistent county aggregations.

The index measure is admittedly not perfect. Researchers have noted the pitfalls with creating indexes. For example, using indexes can result in a loss of variability and explanatory power through the grouping of data. It also implies that more data are always better. Finally, using all available data, as for version 2.0, ignores concerns about multicollinearity between variables. Many of the data items are redundant.[6] This version of the index shares several of these flaws.

Imperfections aside, the Innovation Index version 2.0 presents a state-of-the-art measure of county and regional innovation performance and capacity. This index can serve as a valuable tool for policymakers and practitioners to quickly evaluate innovative capacity and potential. As with all indexes, however, the overall estimate is not as important as the sum of its parts. Economic development practitioners not only get a quick snapshot of how their region is doing in terms of innovation with the headline index, but they also have the ability to drill down and get dirty in the data to gain a better understanding about their region's strengths and weaknesses.

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Proprietorship

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Economic Well-Being Index

Per Capita Personal Income Growth

1. Center for Regional Development, Indiana Business Research Center, Center for Regional Competitiveness, Strategic Development Group, Inc., & Economic Modeling Specialists, Inc. (2009*). Crossing the next regional frontier: Information and analytics linking regional competitiveness to investment in a knowledge-based economy*. Retrieved from http://www.statsamerica.org/innovation/reports/crossing_regional_frontier_full_report.pdf

Compensation

1. Center for Regional Development, Indiana Business Research Center, Center for Regional Competitiveness, Strategic Development Group, Inc., & Economic Modeling Specialists, Inc. (2009*). Crossing the next regional frontier: Information and analytics linking regional competitiveness to investment in a knowledge-based economy*. Retrieved from http://www.statsamerica.org/innovation/reports/crossing_regional_frontier_full_report.pdf

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Average Poverty Rate

1. Center for Regional Development, Indiana Business Research Center, Center for Regional Competitiveness, Strategic Development Group, Inc., & Economic Modeling Specialists, Inc. (2009*). Crossing the next regional frontier: Information and analytics linking regional competitiveness to investment in a knowledge-based economy*. Retrieved from http://www.statsamerica.org/innovation/reports/crossing_regional_frontier_full_report.pdf

Average Unemployment Rate

1. Center for Regional Development, Indiana Business Research Center, Center for Regional Competitiveness, Strategic Development Group, Inc., & Economic Modeling Specialists, Inc. (2009*). Crossing the next regional frontier: Information and analytics linking regional competitiveness to investment in a knowledge-*

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Dependency Ratio–Measured by Income Sources

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3. Coulson, A. J. (2014). *State education trends: Academic performance and spending over the past 40 years* (Policy Analysis 746). Washington, DC: Cato Institute.
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1. Center for Regional Development, Indiana Business Research Center, Center for Regional Competitiveness, Strategic Development Group, Inc., & Economic Modeling Specialists, Inc. (2009*). Crossing the next regional frontier: Information and analytics linking regional competitiveness to investment in a knowledge-based economy*. Retrieved from http://www.statsamerica.org/innovation/reports/crossing_regional_frontier_full_report.pdf

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Institutionally-Based Startups

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3. Almeida, P., & Kogut, B. (1997). The exploration of technological diversity and geographic localization in innovation: Start-up firms in the semiconductor industry. *Small Business Economics, 9*(1), 21–31.
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15. Porter, M. E. (1990). *The competitive advantage of nations*. New York, NY: Free Press.
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1. Rosenbloom, J. L. (2007). The geography of innovation commercialization in the United States during the 1990s. *Economic Development Quarterly, 21*(1), 3–16.
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Kauffman Entrepreneurship Index

1. Hafer, R. W. (2013). Entrepreneurship and state economic growth. *Journal of Entrepreneurship and Public Policy*, *2*(1), 67–79.
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Business Formation and Survival

1. Clayton, R. L., & Spletzer, J. R. (2009). Business employment dynamics. In T. Dunne, J. B. Jensen, & M. J. Roberts (Eds.), *Produce dynamics: New evidence from micro data* (pp. 125–147). Chicago, IL: University of Chicago Press.

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Volunteer Rate

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Appendix A: Measure Operationalization

Dear Reader,

Please note: Given the wide array of measures and that several important measures are sparse—venture capital has many zeros or missing values, for example—the index is constructed for inter-regional (or county) comparisons for one time period only and for one regional category only. An MSA ranking can only be compared with another MSA and a county with another county. The U.S. value is not equal to 100 (or one) and can can change year to year. For a regional definition—county, MSA, economic development district, etc.—the U.S. value is dependent upon the values for that array of data. Please see the "Index Calculation" section on page 13 for more details on the index calculation.

Comprehensive Presentation of Formulas for the Innovation Measures

Table 5: Recurring Abbreviations

Variable	Description
g	Region*
c	County
Ng	Number of Counties in Region g
st	State
t	Year
lya	Last Year Available
ttl	Total
d	Distance
pop	Population

* Note: If the region is only one county, we replace *g* by county *c*.

Human Capital and Knowledge Creation Index

“Salad Days” Population, Ages 25-44, Annual Average Growth Rate

Average annual growth rate for mid-aged (25 to 44 years old) population using yearly Census estimates from 2002 to the latest year available. *Source: U.S. Census Bureau, Federal-State Cooperative for Population Estimates (FSCPE).*

$$popMAr_g = \frac{ln\left(pop25to44^{FSCPE}_{g,t=lya}\right) - ln\left(pop25to44^{FSCPE}_{g,t=2002}\right)}{lya - 2002}$$

pop25to44 = FSCPE mid-aged population (25–44)

Educational Attainment

High School Attainment

Percent of population ages 18 to 24 years with a high school diploma. *Source: U.S. Census Bureau American Community Survey (ACS).*

$$edHS_g = \frac{\sum_{c=1}^{Ng} \sum[pop18to24^{ACS}_{c,lya} - noHSatt^{ACs}_{c,lya}]}{\sum(pop18to24^{ACS}_{c,lya})} \times 100$$

noHSatt = ACS population ages 18 to 24 years without a high school diploma
pop18to24 = ACS population ages 18 to 24 years

Some College

Percent of population ages 25 years and older with some college. *Source: U.S. Census Bureau American Community Survey (ACS).*

$$edsomecol_g = \frac{\sum_{c=1}^{Ng} somecol^{ACS}_{c,lya}}{\sum_{c=1}^{Ng} pop25abv^{ACS}_{c,lya}} \times 100$$

somecol = ACS population ages 25 years and older with some college
pop25abv = ACS population 25 years and older

Associate Degree

Percent of population ages 25 years and older with an associate degree. *Source: U.S. Census Bureau American Community Survey (ACS).*

$$edassc_g = \frac{\sum_{c=1}^{Ng} assc_{c,lya}}{\sum_{c=1}^{Ng} pop25abv_{c,lya}} \times 100$$

assc = ACS population ages 25 years and older with an associate degree
pop25abv = ACS population 25 years and older

Bachelor's Degree

Percent of population ages 25 years and older with a bachelor's degree. *Source: U.S. Census Bureau American Community Survey (ACS).*

$$edbach_g = \frac{\sum_{c=1}^{Ng}\left[bach_{c,lya}^{ACS}\right]}{\sum_{c=1}^{Ng} pop25abv_{c,lya}^{ACS}} \times 100$$

bach = ACS population ages 25 years and older with a bachelor's degree
pop25abv = ACS population 25 years and older

Graduate Degree

Percent of population ages 25 years and older with a graduate, professional or other post-bachelor's degree. *Source: U.S. Census Bureau American Community Survey (ACS).*

$$edgrad_g = \frac{\sum_{c=1}^{Ng} grad_{c,lya}^{ACS}}{\sum_{c=1}^{Ng} pop25abv_{c,lya}^{ACS}} \times 100$$

grad = ACS population ages 25 years and older with a graduate, professional or other post-bachelor's degree
pop25abv = ACS population 25 years and older

Knowledge Creation and Technology Diffusion

Patent Technology Diffusion

For the index measure, we include the last three years available based on the patent issue date and not the application date. Indeed, some patents who filed within the last three years might not have been granted yet and, therefore, are not present in the data set. For each region, in the last three years available, we average the diffusion score of all patents in a region in one year by the total number of patents. Then, we average that score across the last three years available. *Source: U.S. Patent and Trademark Office (USPTO).*

To calculate the aggregate score, we first removed from our data set all design patents, recalled patents, statutory invention registrations, and all patents with missing values for the number of citations. For this diffusion score, we also dropped all patents from the years 2011 and 2012 because, at the time of this writing, these patents had almost no citations. Over time, as these years' patents were increasingly cited, the diffusion index could be subject to large swings that were not related to diffusion rates.

In order to create a measure reliable over the years, we have calculated how each patent deviates from the mean number of citations (*r*) and mean number of unique classes per citation (*s*) for that year. This first measure of diffusion ranges from -2 to 143.

For each patent *pat*:

$$diff_{pat} = \left(\frac{r_{pat} - \bar{r}}{\bar{r}}\right) + \left(\frac{s_{pat} - \bar{s}}{\bar{s}}\right)$$

Patents were then assigned to categories. We started using Hall, Jaffe and Trajtenberg's classes (2001) and updated them in order to have finer distinctions between classes and include newer patent technologies. For each patent, we match their class with the corresponding IBRC category code and assign them the relevant diffusion score (see Appendix B for Jaffe patent class assignments). **Table 6** provides the scores assigned to each of the IBRC categories. The average score for each category is between -1 and 1. Higher values mean that the patents in these categories have more citations and more diversity in their citations than the average patent of that year.

Table 6: Major Patent Technology Categories

IBRC Category	Category Title	Diffusion Score (*catdiff*)
1	Chemicals, Including Coatings, Except Pharma	-0.4104
2	Communications	0.2750
3	Computers, Information Technology and Data Processing	0.3487
4	Bio-Tech and Pharmaceuticals	-0.6678
5	Electronics and Electrical	-0.0575
6	Mechanical	-0.2367
7	Transportation, Material Transfer and Storage	-0.2434
8	Agriculture and Natural Resources	-0.4565
9	Building, Construction Materials and Methods	-0.0331
10	Power Generation and Other Industrial, Including Armaments	-0.0307
11	Consumer Goods, Including Furniture	-0.0432
12	Medical Devices and Medical Practices	0.7026

Source: Indiana Business Research Center

According to these scores, some categories of patents have a wide and diverse reach. Indeed, medical device patents, computers and communications have the highest diffusion scores. Their patents tend to be cited a lot and across various fields. On the other hand, chemicals, agriculture and bio-tech patents are less cited and/or only cited by patents in one class.

For each region g for the last three years years available, we multiply the number of patents in one category and in that region by the diffusion score of that category. We then add the values for all the categories present in that region. Then, we average it by the number of patents in that region:

$$patdiff_g = \frac{\sum_{cat=1}^{ttlcat}(catdiff_t^{cat} * patcount_g^{cat})}{\sum_{cat=1}^{ttlcat} patcount_g^{cat}}$$

catdiff = IBRC category diffusion score
patcount= number of patents in IBRC category cat and in region g
ttlcat = Total number of categories (12)

University-Based Knowledge Spillovers, Science and Engineering

Knowledge spillovers are measured using university research and development (R&D) spending and distance between the university and the county or region selected. We only add the R&D spending in the following fields: engineering, geosciences, life sciences, math and computer science, and physical science. Higher scores indicate regions close to universities with high R&D spending in science and engineering fields. This measures how scientific knowledge spreads from universities to neighboring regions. Because of some inconsistencies in the data, our research team had to recode the ZIP codes for some universities to match their official addresses. *Source: National Science Foundation (NSF).*

Following previous research on geographic spillover of R&D research, we weigh university R&D spending by an exponentially decreasing function of the distance. We take the sum of all university R&D spending in the data set and weigh them using the exponential of the negative distance between the university and the county selected. However, in order to be parsimonious, we include a cutoff point of 50 miles. To avoid dealing with very small numbers, we divide the distance by 100 miles before taking the exponential ($RD_{c_2,t}$).

First, we multiply all the university R&D values by 1,000 in order to get values in real dollars instead of in thousands of dollars. We add the total R&D spending for each county.

Then, each county's spillover score is the sum of the R&D spending in counties within 50 miles weighted by a decay function. For each county *c* with *ttlc* counties within 50 miles, and for each year of the last three years available, we calculate the knowledge spillover score using the natural log of R&D spending total for all universities in the second county and the decay function ($e^{-dst/100}$).

$$Kspl_{c,t} = \sum_{u=1}^{ttlc} [ln(1{,}000 \times RD_{c_2,t} + 1) \times e^{-(dst/100)}]$$

RD_{c2} = Total R&D spending for all universities in county c_1 in engineering, geosciences, life sciences, math and computer science, and physical science in thousands of dollars for each of the three years available
dst = Distance between county c and county c_2
(if the region and the university are in the same region, dst=0)

Then, for each county *c*, we calculate the county-level knowledge spillover score:

$$Kspl_c = \frac{\sum_{t=lya-2}^{t=lya} Kspl_t}{3}$$

Finally, for each region g with *Ng* counties, we calculate the regional knowledge spillover score:

$$Kspl_g = \frac{\sum_{c=1}^{Ng} Kspl_c}{Ng}$$

Business Incubator Spillovers

We use the total number of business incubators within 50 miles to calculate the business incubator score. The distance decay weight ($e^{-(dst/50)}$) ranges from 0 to 1. Business incubators with the same contact person and the same phone number were considered duplicates and deleted from the data set. *Source: National Business Incubation Association and a special tabulation of data from a survey of business incubators, courtesy of Professor David A. Lewis at the University at Albany, State University of New York*

For each county *c* with *ttlincbt* incubators within 50 miles, and for the last year available, calculate the business incubator score:

$$incbtspl_{c,lya} = \sum_{incbt=1}^{ttlincbt_{lya}} 10\times e^{-(dst^{incbt}/50)}$$

dst^{incbt}= Distance between county c and incubator in miles
ttlincbt = Total number of incubators within 50 miles
(if the region and the incubator are in the same region, dst^{incbt}=0)

Finally, for each region with *Ng* counties:

$$incbtspl_g = \frac{\sum_{c=1}^{Ng} incbtspl_c}{Ng}$$

STEM Education and Occupations

STEM Degree Creation

We measure the total STEM degrees awarded from institutions in a county or region at the bachelor's, master's and doctorate level, scaled to population (per 1,000 individuals averaged across the last three years available). **Table 7** shows the complete list of STEM degrees included in this measure with their CIP codes. *Source: Integrated Postsecondary Education Data System (IPEDS).*

Table 7: Classification of Instructional Programs (CIP) Codes for STEM Degrees

CIP Code	Field of Study
11	Computer and Information Sciences and Support Services
14	Engineering
15	Engineering Technologies and Engineering-Related Fields
26	Biological and Biomedical Sciences
27	Mathematics and Statistics
30.01	Biological and Physical Sciences
30.08	Mathematics and Computer Science
30.10	Biopsychology
30.15	Science, Technology and Society
40	Physical Sciences
41	Science Technologies/Technicians

Source: Integrated Postsecondary Education Data System

For each region with *Ng* counties, we calculate the number of STEM graduates per 1,000 for the last three years available divided by the sum of the population in the last three years:

$$STEM2pop_{g,t} = \frac{\sum_{c=1}^{Ng} ttlSTEM_{c,t}}{\sum_{c=1}^{Ng} pop_{c,t}^{ACS}} \times 1{,}000$$

ttlSTEM = Total number of graduates in STEM fields at all levels
pop = ACS Population
t: Last three years available

Technology-Based Knowledge Occupation Clusters

The technology-based knowledge occupation clusters (*TCKempcl*) are based on the research team’s cluster analysis, which replaces the cluster definitions used in version 1 of the Innovation Index. This measure includes the following eight clusters: engineering, architecture and related disciplines (#2); health care–life and medical scientists (#4); health care–medical practitioners and scientists (#5); information management and computing (#8); mathematics, statistics, data analysis and accounting (#10); natural sciences and environmental management (#11); postsecondary education and knowledge creation (#12); and STEM and applied science technicians (#14). *Source: IBRC Occupational Employment Statistics-based occupation estimates.*

Table 8 presents the occupation cluster definitions. Appendix B presents the equivalence between Standard Occupational Classification codes and clusters and the NAICS cluster assignments based on Porter's Cluster Mapping Project (2008).

Table 8: Occupation Cluster Definitions

Cluster Number	Cluster Title
	Knowledge-Based Clusters
01	Arts, Entertainment and Broadcasting Specialists and Management
02*	Engineering, Architecture and Related Disciplines
03	Finance, Legal, and Real Estate
04*	Health Care: Life and Medical Scientists
05*	Health Care: Medical Practitioners and Scientists
06	Health Care: Nurses and Specialized Care Delivery
07	Health Care: Therapy, Counseling and Rehabilitation
08*	Information Management and Computing
09	Managerial, Sales, Marketing and Human Resources
10*	Mathematics, Statistics, Data Analysis and Accounting
11*	Natural Sciences and Environmental Management
12*	Postsecondary Education and Knowledge Creation
13	Primary, Secondary and Vocational Education, Remediation and Social Services
14*	STEM and Applied Science Technicians
15	Transportation, Logistics and Planning
	Skills-Based Clusters
16	Administration and Office Support
17	Artisans, Craftsman, Designers, including Performance
18	Attendants and General Services
19	Construction Trades
20	Facility, Plant and Large Equipment Operators and Technicians
21	Financial, Legal and Inspection Services, Support
22	Food Preparation and Service
23	Health Care: Therapists, Technicians and Aides
24	Machinists and Skilled Operators and Tenders
25	Managers and First-line Supervisors
26	Mechanics and Repair Technicians
27	Media, Web Development and Programming

Cluster Number	Cluster Title
28	Personal Services
29	Production Operators and Tenders
30	Production, General
31	Safety, Security and Emergency
32	Sales, Agents, Brokers and Customer Relations, Support
33	Transportation Equipment Operators
34	Transportation, Logistics and Dispatch, Support

* An asterisk indicates a technology-based knowledge occupation cluster.
Source: IBRC Occupational Employment Statistics-based occupation estimates and IBRC cluster analysis using O*NET

$$TCKempcl_g = \frac{TCKemp_{g,lya}}{ttlemp_{g,lya}^{OES}}$$

*TCKemp = Technology-based knowledge occupation employment**
ttlemp =IBRC OES total employment
** Requires aggregation of the eight technology-based knowledge occupation clusters*

High-Tech Industry Employment Share

In contrast to the above occupation counts in high-tech, this metric measures the innovative capacity of the region on an industry basis. High-tech industry employment share measures an aggregation of employment in key sectors (e.g., telecommunications, Internet providers, scientific laboratories) as the average high-tech employment share of total employment from 2002 to the latest year available. *Source: IBRC QCEW-complete employment estimates.*

$$avgHTsh_g = \frac{\sum_{t=2002}^{lya} HTemp_{g,t}}{\sum_{t=2002}^{lya} ttlemp_{g,t}^{QCEW}}$$

HTemp = IBRC high-tech employment
ttlemp = IBRC QCEW total employment

Table 9 presents the high-tech industries based on a more restrictive "percent of industry with high-tech occupations" threshold used by Heckler (2005). While it employs a high percentage of high-tech occupations—usually considered to be STEM disciplines like computer science, mathematics and economics in this industry's case—we deleted the industry "Monetary authorities, central bank" because it is highly concentrated in a handful of regions—as in branches of the Federal Reserve—and tends to provide false positives for above national average in terms of the presence of small establishments.

To simplify the presentation of the data, we aggregated the four-digit industries into major high-tech categories. While these broader categories may appear similar to other NAICS aggregates, for example three-digit NAICS, or industry clusters a la Porter (2008), the aggregations have no direct linkage to either classification methodology. One might say that they are incomplete aggregations within the NAICS framework.

Table 9: High-Tech Industries by Four-Digit NAICS Definitions with Their Broad Industry Category

Broad Industry Category (BIC)	NAICS	Industry
Chemical Manufacturing	3251	Basic Chemical Manufacturing
	3252	Resin, Synthetic Rubber, and Artificial Synthetic Fibers and Filaments
	3254	Pharmaceutical and Medicine Manufacturing
	3255	Paint, Coating, and Adhesive Manufacturing
	3259	Other Chemical Product and Preparation Manufacturing
Machinery and Equipment	3332	Industrial Machinery Manufacturing
	3333	Commercial and Service Industry Machinery Manufacturing
	3336	Engine, Turbine, and Power Transmission Equipment Manufacturing
	3339	Other General Purpose Machinery Manufacturing
Computer and Communication Manufacturing	3341	Computer and Peripheral Equipment Manufacturing
	3342	Communications Equipment Manufacturing
	3343	Audio and Video Equipment Manufacturing
Electrical and Optical Manufacturing	3344	Semiconductor and Other Electronic Component Manufacturing
	3345	Navigational, Measuring, Electro Medical, and Control Instruments
	3346	Manufacturing and Reproducing Magnetic and Optical Media
	3353	Electrical Equipment Manufacturing
Aerospace Product and Parts Manufacturing	3364	Aerospace Product and Parts Manufacturing
Communications	5112	Software Publishers
	5171	Wired Telecommunications Carriers
	5172	Wireless Telecommunications Carriers (Except Satellite)
	5174	Satellite Telecommunications

Broad Industry Category (BIC)	NAICS	Industry
	5179	Other Telecommunications (Including Resellers in 07 & 12)
Data and Internet	5182	Data Processing, Hosting, and Related Services
	5191	Internet Publishing and Broadcasting and Web Search Portals
Architectural, Engineering, and Related Services	5413	Architectural, Engineering, and Related Services
Scientific and Technical Services	5415	Computer Systems Design and Related Services
	5416	Management, Scientific, and Technical Consulting Services
	5417	Scientific Research and Development Services
Management of Companies and Enterprises	5511	Management of Companies and Enterprises

Source: IBRC QCEW-complete employment estimates and Heckler (2005)

Business Dynamics Index

Establishment Formation and Dynamics

The source of these churn statistics is the Statistics of U.S. Businesses data set from the U.S. Census Bureau. The data are available at the two-digit industry detail level for counties. (More current dynamics statistics are available from the U.S. Bureau of Labor Statistics, but they are only available at the state level.)

Since 2008, employment change or dynamics data include the number of establishments and the corresponding employment change for births, deaths, expansions and contractions. The data are tabulated by geographic area, industry and enterprise employment size. Industry classification is based on the 2007 NAICS codes presented in **Table 10**. An establishment with 0 employment is an establishment with no paid employees in the mid-March pay period but with paid employees at some time during the year. Employment by births, deaths, expansions and contractions is available beginning in 2008 (showing change between 2007 and 2008). The data from 2000-2007 only provides change in the number of establishments.

Table 10: Two-Digit 2007 NAICS Codes and Two-Digit High-Tech Industries

Sector	Description
11	Forestry, Fishing, Hunting, and Agriculture Support
21	Mining
22	Utilities
23	Construction
31-33*	Manufacturing
42	Wholesale Trade
44-45	Retail Trade
48-49	Transportation and Warehousing
51*	Information
52	Finance and Insurance
53	Real Estate and Rental and Leasing
54*	Professional, Scientific, and Technical Services
55*	Management of Companies and Enterprises
56	Administrative and Support and Waste Management and Remediation Services
61	Educational Services
62	Health Care and Social Assistance
71	Arts, Entertainment, and Recreation
72	Accommodation and Food Services
81	Other Services (except Public Administration)
99	Unclassified

* Sectors with an asterisk are considered traded, high-tech sectors.
Source: Indiana Business Research Center (the assignment of two-digit industries as high-tech is based on the four-digit high-tech industries in Table 9).

Establishment Births to Total Establishments

This is the ratio between total births of establishments and total establishments in a region in the last year available, for all industry sectors. *Source: U.S. Census Bureau.*

$$estBr_g = \frac{\sum_{c=1}^{Ng} B_{c,lya}}{\sum_{c=1}^{Ng} ttlest_{c,lya}}$$

B: Establishment births
D: Establishment deaths
X: Establishment expansions
C: Establishment contractions
no∆: Establishment constants (no change)‡
ttlest: Establishment total at the beginning of year t (D+X+C+ no∆) ‡

‡noΔ (constant) is only available in the data set until 2007 (included). After 2007, the total number of establishments at the beginning of the year is directly provided.

Traded Sector Establishment Births to Total Establishments

This is the ratio of establishment births for high-tech traded sectors to total establishments in those sectors, for the last year available in region *g*. The included sectors (with NAICS codes) are manufacturing (31-33); information (51); professional, scientific, and technical services (54); and management of companies and enterprises (55). *Source: U.S. Census Bureau.*

$$esttrBr_g = \frac{\sum_{c=1}^{Ng} trB_{c,lya}}{\sum_{c=1}^{Ng} ttltrest_{c,lya}}$$

trB: Traded, high-tech, establishment births
ttltrest: Traded, high-tech, total establishments

Jobs Attributed to Births to Total Employment

Jobs from births of establishments divided by the total jobs in region g in the last year available. *Source: U.S. Census Bureau.*

$$jobBr_g = \frac{\sum_{c=1}^{Ng} jobB_{c,lya}}{\sum_{c=1}^{Ng} ttljob_{c,lya}}$$

ttljob: Job total at the beginning of the last year available
jobB: Jobs associated with establishment births (B)

Change in Establishment Births to Total Establishments

We take a three-year average at the beginning and the end of the 10-year time period to reduce the cyclical influences on establishment formation. In other words, *estBd* is a rate at the end of the period divided by the rate at the beginning. It is calculated as the sum of births to the sum of all establishments over the last three years available of the time frame *(lya-2* to *lya)* divided by the sum of births to the sum of all establishments over the first three years of the 10-year time frame *(lya-10* to *lya-8*). *Source: U.S. Census Bureau.*

$$estBd_g = \left(\frac{\left(\sum_{c=1}^{Ng} \sum_{t=lya-2}^{lya} B_{c,t} \right)}{\sum_{c=1}^{Ng} \sum_{t=lya-2}^{lya} ttlest_{c,t}} \right) \div \left(\frac{\left(\sum_{c=1}^{Ng} \sum_{t=lya-10}^{lya-8} B_{c,t} \right)}{\sum_{c=1}^{Ng} \sum_{t=lya-10}^{lya-8} ttlest_{c,t}} \right)$$

B: Establishment births
D: Establishment deaths
X: Establishment expansions
C: Establishment contractions
noΔ: Establishment constants (no change)‡

ttlest: Establishment total at the beginning of year t (D+X+C+ noΔ) ‡

‡noΔ (constant) is only available in the data set until 2007 (included). After 2007, the total number of establishments at the beginning of the year is directly provided.

Establishment Expansions Divided by Contractions

The ratio of the total expansions by the contractions for all industry sectors, for the last year available in the region. *Source: U.S. Census Bureau.*

$$estX2C_g = \frac{\sum_{c=1}^{Ng} X_{c,lya}}{\sum_{c=1}^{Ng} C_{c,lya}}$$

X: Establishment expansions
C: Establishment contractions

Establishment Births Divided by Deaths

The ratio of the establishments births by the establishment deaths for all industry sectors, for the last year available in the region. *Source: U.S. Census Bureau.*

$$estB2D_g = \frac{\sum_{c=1}^{Ng} B_{c,lya}}{\sum_{c=1}^{Ng} D_{c,lya}}$$

B: Establishment births
D: Establishment deaths

Traded Sector Establishment Dynamics

This ratio, for the last year available *t*, for counties in region *g*, is calculated as (births plus expansions) divided by (deaths plus contractions) for the high-tech sectors. The included sectors (with NAICS codes) are manufacturing (31-33); information (51); professional, scientific, and technical services (54); and management of companies and enterprises (55). *Source: U.S. Census Bureau.*

$$trestdyna_g = \frac{\sum_{c=1}^{Ng} \mathrm{trB}_{\mathrm{c,lya}} + \sum_{c=1}^{Ng} \mathrm{trX}_{\mathrm{c,lya}}}{\sum_{c=1}^{Ng} \mathrm{trD}_{\mathrm{c,lya}} + \sum_{c=1}^{Ng} \mathrm{trC}_{\mathrm{c,lya}}}$$

trB: Traded, high-tech, establishment births
trD: Traded, high-tech, establishment deaths
trX: Traded, high-tech, establishment expansions
trC: Traded, high-tech, establishment contractions

Venture Capital, Dollar and Count Measures

Our VC investment data come from the Thomson One database, which contains information on total VC investments, VC investments by industry, distribution by stage of financing and whether the company has undergone an IPO. Stage definitions are provided by PricewaterhouseCoopers.

There were many issues regarding the raw data. For example, a firm may have received several tranches of VC, but the database only presents the total, as of the date of the data pull. Thus, one does not have a year-by-year time series of VC flows into a location. This was "solved" by averaging the total (from 2014 data) by the number of VC years of funding. That is, to calculate the values in the date field, "*Funding for Year (Total Funding to Date/YwF)*," a company's ID number is looked up and the number of years for which there is a record of funding ["*Years with Funding (YwF)"*] is summed. The total funding value ("*Total Funding to Date"*) is then divided by that number of years to provide an annual average funding for that company.

The database also provides the stage of the company at the time of the funding events, but the data fields (there were three for the stage) were not always helpful. The field "*Company Investment Stage 2 at Round Date"* is the field used to know the stage of the funding and calculate VC by expansion stage. The data file also provided a "round number" for the round of financing, but this field was not used.

For all measures of VC, the dollar value reported will consist of 10-year averages of the averages in the field *Funding for Year (Total / YwF)*, with the exception of the change in venture capital. The first year (2000) will remain fixed until the next upgrade, but the last year will be updated as new data are released. The rationale for using years earlier than the 10-year average of averages is to show whether the trend for VC in the county/region has increased or decreased.

There are seven measures under the VC rubric, but they are grouped based on whether they are dollar or count values. Both the dollar measures and the count measures are scaled to the region's (or county's) current-dollar GDP over the relevant time period, $cuGDP_t$. The change measures are not scaled. *Source: Thomson One and IBRC current-dollar GDP estimates by county.*

Average Annual Venture Capital

First, we compute the total of all venture capital in dollars for all counties in region *g* over the 10-year time period.

$$VC\$_g = \sum_{c=1}^{Ng} \sum_{t=lya-9}^{lya} VC\$_{c,t}$$

VC$: Venture capital, dollars

Then, the average annual venture capital is equal to VC$_g$ divided by the number of years in the time series (10 in this case).

$$avgVC\$_g = \frac{VC\$_g}{Nyr}$$

Nyr: Number of years in time span=10

Finally, we scale the average annual venture capital by the current-dollar average GDP for the applicable time period:

$$VC2GDP_g = \frac{avgVC\$_g}{avgGDPcu_g}$$

avgGDPcu: Average current-dollar GDP in billions (over the applicable time period)

Venture Annual Capital by Expansion Stage

First, we calculate the average annual VC in dollars for expansion stage for all counties in region g over the last 10 years available.

$$VCXstg_g = \frac{\sum_{t=lya-9}^{lya} VC\$_{g,t}^{ExpStg}}{Nyr}$$

$VC\$_g^{ExpStg:}$: Expansion stage funding (Company Investment Stage 2 at Round Date, value = Expansion).

Then, we scale this value by the region's current-dollar average GDP:

$$VCX2GDP_g = \frac{VCXstg_g}{avgGDPcu_g}$$

Venture Annual Capital by High-Tech Industry

First, we calculate the average annual VC in dollars for high-tech firms in region *g* over the last 10 years available.

$$VCHT_g = \frac{\sum_{t=lya-9}^{lya} VC\$_{g,t}^{tech}}{Nyr}$$

$VC\$_g^{tech}$= Funding for high-tech industries (NAICS: all six-digit industries within the four-digit high-tech industry set shown in **Table 9**)

Then, we scale this value by the region's average current-dollar GDP:

$$VCHT2GDP_g = \frac{VCHT_g}{avgGDPcu_g}$$

Change in Venture Capital

We calculate the change in VC funding from the total VC funding from 2000 through 2003 to the total VC funding from the last four years available in region g. (Using either total or average would make no difference in the result.)

$$VC\$d_g = \frac{VC\$_{g,te} - VC\$_{g,tb}}{VC\$_{g,tb}}$$

Where *te* represents the last four years of the delta period and *tb* is the first four years:

$$VC\$_{g,te} = \sum_{c=1}^{Ng} \sum_{t=lya-3}^{lya} VC\$_{c,t}$$

$$VC\$_{g,tb} = \sum_{c=1}^{Ng} \sum_{t=b}^{(b+3)} VC\$_{c,t}$$

b: First year of delta period (2000) (Investment Year)

Initial Public Offerings (IPOs)

The IPO data are pulled as a query from the data set (the count of distinct companies that have an IPO value in a 10-year time frame).

Then, the total number of IPOS is scaled to (divided by) the region's average current-dollar GDP:

$$VCIPO2GPD_g = \frac{VCIPO_g}{avgGDPcu_g}$$

$VCIPO_g$: Total number of Initial Public Offerings in region g over the time period t

Average Annual Venture Capital Deals

The total of all venture capital deals for all counties in region g over the time period t is equal to the sum of VC deals divided by the number of years in the time series (10 in this case).

$$VCDeal_g = \sum_{c=1}^{Ng} \sum_{t=lya-9}^{lya} VCDeal_{c,t}$$

VCDeal: Venture capital, deals

$$avgVCDeal_g = \frac{VCDeal_g}{Nyr}$$

We then scale the average annual venture capital deals to the region's average current-dollar GDP:

$$VCDeal2GDP_g = \frac{avgVCDeal_g}{avgGDPcu_g}$$

Change in Venture Capital Deals

We first calculate the change—*d* for delta—in the number of VC deals from the total VC deal count from 2000 through 2003 to the total VC deal count from the last four years available in region *g*. (Using either total or average would make no difference in the result.)

$$VCDeald_g = \frac{VCDeal_{g,te} - VCDeal_{g,tb}}{VCDeal_{g,tb}}$$

Where *te* represents the last four years of the delta period and *tb* is the first four years:

$$VCDeal_{g,te} = \sum_{c=1}^{Ng} \sum_{t=(lya-3)}^{lya} VCDeal_{c,t}$$

$$VCDeal_{g,tb} = \sum_{c=1}^{Ng} \sum_{t=b}^{(b+3)} VCDeal_{c,t}$$

b: First year of delta period (2000) (Investment Year)

Business Profile Index

Foreign Direct Investment Attractiveness

The FDI data used in this analysis is related to greenfield investments and plant and equipment expansions. This concept does not include the majority of FDI flows that are related to mergers and acquisitions. These data are announced FDI investments that may or may not be realized. The data are treated, however, as though all announcements are realized. Data are three-year moving averages. FDI (announcement) flows include intrastate deals, i.e., a California firm moving to Indiana, but that is perfectly fine for the purposes of measuring FDI attractiveness. Using the FDI data based on the number of employees expected and the dollar value of the investment, we calculate four indexes: one pair focused on investment from other states in the U.S. and one pair analyzing investment from other countries. *Source: fDi Markets and the U.S. Census Bureau American Community Survey (ACS).*

FDI Employment Index, Foreign Source

First, we calculate FDI employment from a foreign source as the ratio of new FDI employment for region *g* over the three-year period per thousand of the working-age population (defined as the population between ages 18 and 66).

$$FDIemp2labF_g = \frac{\sum_{t=lya-2}^{lya} FDIempF_{g,t}}{\sum_{t=lya-2}^{lya} lab_{g,t}^{ACS}} \times 1{,}000$$

FDIempF: Foreign FDI employment announcements
lab: ACS working-age population, defined as those between ages 18 and 66

To derive the index for region *g*, one normalizes the region's values with the U.S. values and multiplies by 100.

$$FDIempF2US_g = \left({FDIemp2labF_g}/{FDIemp2labF_{US}} \right) \times 100$$

FDI Employment Index, National Source

We calculate FDI employment from U.S. sources as the ratio of new FDI employment for region *g* over the three-year period per thousand of the working-age population (defined as the population between age 18 and 66).

$$FDIemp2labUS_g = \frac{\sum_{t=lya-2}^{lya} FDIempUS_{g,t}}{\sum_{t=lya-2}^{lya} lab_{g,t}^{ACS}} \times 1{,}000$$

FDIempUS: U.S. FDI employment announcements
lab: ACS working-age population, defined as those between ages 18 and 66

To derive the index for region *g*, one normalizes the region's values with the U.S. values and multiplies by 100.

$$FDIempUS2US_g = \left({FDIemp2labUS_g}/{FDIemp2labUS_{US}} \right) \times 100$$

FDI Investment Index, Foreign Source

We calculate FDI dollar investment from foreign sources as the ratio of average new FDI investment for region *g* over the three-year period per thousand of the working-age population (defined as the population between 18 and 66).

$$FDIinv2labF_g = \frac{\sum_{t=lya-2}^{lya} FDIinvF_{g,t}}{\sum_{t=lya-2}^{lya} lab_{g,t}^{ACS}} \times 1{,}000$$

FDIinvF: Foreign FDI investment (in millions of $) announcements
lab: ACS working-age population, defined as those between ages 18 and 66

To derive the index for region *g*, one normalizes the region's values with the U.S. values and multiplies by 100.

$$FDIinvF2US_g = \left({FDIinv2labF_g}/{FDIinv2labF_{US}} \right) \times 100$$

FDI Investment Index, National Source

We calculate FDI dollar investment from U.S. sources as the ratio of average new FDI investment for region *g* over the three-year period per thousand of the working-age population (defined as the population between 18 and 66).

$$FDIinv2labUS_g = \frac{\sum_{t=lya-2}^{lya} FDIinvUS_{g,t}}{\sum_{t=lya-2}^{lya} lab_{g,t}^{ACS}} \times 1{,}000$$

FDIinvUS: U.S. FDI investment (in millions of $) announcements
lab: ACS working-age population, defined as those between ages 18 and 66

To derive the index for region *g*, one normalizes the region's values with the U.S. values and multiplies by 100.

$$FDIinvUS2US_g = \left({FDIinvF2US_g}/{FDIinvF2US_{US}} \right) \times 100$$

Connectivity

Broadband Density and Penetration

The Innovation Index reports both a snapshot of the current "state of the art" connectivity capacity and speed of a region, as well as the overall trend of the average household adopting high-speed Internet connections. *Source: Federal Communications Commission (FCC).*

The first snapshot measure adopts the latest definition of the upper end of broadband capacity as defined, collected and reported by the FCC. The technology has and is expected to rapidly change, so only the last year of available data is used. Given one cannot expect consistency from one year to the next, the curious user can look up the latest definitions on the FCC website.[7] Each revision of the Innovation Index will likely have a different definition. Given that the primary application for the index is inter-region, the changing definition over time is inconsequential. The second trend measure attempts to track the adoption or diffusion of a standard broadband speed measure over time. That said, the "bottom rung" definition of connectivity may also change over time. Should that be the (likely) case, one can still make inter-regional comparisons for a particular vintage (or update version) of the index. The worry is that users or researchers may use these data as a time series, so we must issue a warning:

> **WARNING**: Do not use the values from the Innovation Index's Connectivity Core Index, the connectivity measures or the FCC data that serve as their foundation for time series analysis. One cannot align these measures to statistically assess their relationship with other stable concepts like GDP per worker or employment over time.

Density of Residential Fixed High-Speed Connections

The snapshot measure of broadband density is the residential fixed high-speed connections at least 3 mbps downstream and at least 768 kbps upstream per 1000 households (at the time of this writing, the end of the year 2013). The FCC data are presented in ranges of connections per household. The IBRC takes the mid-point of each density and assigns that mid-point value to the county. The FCC schema of number of connections per 1,000 households is presented in **Table 11**. For code 5, the pseudo-midpoint is 900.

[7] On the FCC site, https://transition.fcc.gov/wcb/iatd/comp.html, find the heading "Census Tract Information Mapped for Internet Access Services faster than 200 kbps in at least one direction."

Table 11: Data Dictionary for County-Level Data from FCC Form 477, Residential Fixed High-Speed Connections at Least 3 Mbps Downstream, 2013

Code	Connections per 1,000 Households
0	Zero
1	Zero < x <= 200
2	200 < x <=400
3	400 < x <=600
4	600 < x <=800
5	800 < x

Source: FCC, Local Telephone Competition and Broadband Deployment, https://transition.fcc.gov/wcb/iatd/comp.html

This indicator is presented as a one-year value for the last year of available FCC data. Because the FCC already scales these data for comparability—the number of households—no other adjustment is need. To serve as a guide for future reference—as the speeds will increase and the variable names will change over time—the FCC variable name for this measure for 2013 is *rfc_per_1000_hhs_nbp.* At the risk of being repetitive, this measure is the one-year snapshot and is conceptually different from the annual change data used below. As a result, the variable name is also different from immediately below and will likely change over time. For this measure, the database variable name—to keep query scripts consistent from year to year—is *rfc2HHden*.

Average Annual Change in Residential Fixed High-Speed Connections

The change in broadband density over time, *rfc2HHdend*, is measured by the change in residential fixed high-speed connections over 200 kbps in at least one direction per 1,000 households from 2009 to the last year available. The year 2009 was selected because the definition for that year appeared to best match the last year available (at the time of this writing).

$$rfc2HHdend_g = \frac{ln(rfc2HHden_{lya}) - ln(rfc2HHden_{2009})}{lya - 2009}$$

rfc2HHden = Residential fixed connections over 200 kbps in at least one direction

Online Agriculture

Using U.S. Department of Agriculture's National Agricultural Statistics Service, online agriculture is defined as the percentage of farm operations with Internet access. The total number of farm operations is found by summing the number of farmers who are categorized as full owners, part owners and tenants. The number of farm operations with Internet access includes farms with various types of Internet connections. *Source: U.S. Department of Agriculture (USDA).*

$$onlineagp_g = \frac{\sum_{c=1}^{Ng} onlineag_{c,lya}}{\sum_{c=1}^{Ng} ttlag_{c,lya}}$$

onlineag = Number of farms operations with Internet access
ttlag = Total number of farm operations

Dynamic Industry Profile

Average Small Establishments

This measure shows the average small establishments per 10,000 workers from 2002 to the latest year available. *Source: U.S. Census County Business Patterns (CBP) and U.S. Bureau of Economic Analysis (BEA).*

$$avgSest_g = \frac{\sum_{t=2002}^{lya} Sest_{g,t}}{\sum_{t=2002}^{lya} ttlemp_{g,t}^{BEA}/10{,}000}$$

Sest = CBP small establishments with less than 20 employees (for all industries)
ttlemp = BEA total employment (for all industries)

Average Large Establishments

This measure shows the average large establishments per 10,000 workers from 2002 to the latest year available. *Source: U.S. Census County Business Patterns (CBP) and U.S. Bureau of Economic Analysis (BEA).*

$$avgLest_g = \frac{\sum_{t=2002}^{lya} Lest_{g,t}}{\sum_{t=2002}^{lya} ttlemp_{g,t}^{BEA}/10{,}000}$$

Lest= CBP large establishments with 500 or more employees
ttlemp = BEA total employment for year t

High-Tech Industry Early-in-Life Cycle Establishment Ratio—"Small Quotient"

Using U.S. Census County Business Patterns data, this ratio is calculated by comparing the proportion of small firms (less than 20 employees) to the national value for a particular high-tech industry weighted by the proportion of firms in that industry. The score range varies from year to year depending on the national quotient for each industry. For 2012, the score ranged from 0 to 2.1. A value of 1 would indicate that the region has similar number of small firms than the country for each high-tech industry present. *Source: U.S. Census County Business Patterns data.*

First, we are only including the industries listed in **Table 9.**

Second, for each broad industry category (BIC) within a region, we calculate the proportion of small establishments and compare it to the national value for that BIC.

Specifically, for each region g, we sum all of the small establishments in a BIC and divide it by the total number of establishments in that region and in the relevant BIC. Then we divide this value by the national quotient for that BIC and weight this quotient by the proportion of establishments in that region that are part of the BIC. Finally, we add up the values for all the BICs present in that region.

For each region g (if we are only looking at the county, then we go through the same calculations below with g=county c) and industry, we add the number of firms that have less than 20 employees for each of the last two years available:

$$Sest_{g,t}^{BIC} = emp1to4_{g,t}^{BIC} + emp5to9_{g,t}^{BIC} + emp10to19_{g,t}^{BIC}$$

t: lya and lya-1
emp1to4 = Number of establishments between1 and 4 employees in BIC
emp5to9 = Number of establishments between 5 and 9 employees in BIC
emp10to19 = Number of establishments between10 and 19 employees in BIC

Then, we calculate SQ_t^{BIC}, which is the nationwide number of small firms in each BIC divided by the total number of firms in the same BIC in year t:

$$SQ_t^{BIC} = \frac{Sest_{US,t}^{BIC}}{ttlest_{US,t}^{BIC}}$$

Sest = Number of small establishments in BIC
ttlest = Total number of establishments in BIC

Table 12 presents an example of the national averages for each BIC in 2012, clearly showing the great variance in the size of industry profile among high-tech industries.

Table 12: National Values for the Portion of Establishments with 20 Employees or Less

Broad Industry Category (BIC)	SQ^i_{2012}
Scientific and Technical Services	0.922117
Architectural, Engineering and Related Services	0.884014
Communications	0.797861
Data and Internet	0.785990
Computer and Communication Manufacturing	0.667105
Management of Companies and Enterprises	0.661464
Machinery and Equipment	0.605536
Electrical and Optical Manufacturing	0.594394
Chemical Manufacturing	0.546106
Aerospace Product and Parts Manufacturing	0.476571

Source: IBRC analysis using County Business Patterns and authors definition of high-tech industries.

We calculate $P_{t,g}^{BIC}$, the proportion of high-tech establishments in the region that are part of the Broad Industry Category (BIC) in year *t*:

$$P_{t,g}^{BIC} = \frac{ttlest_{g,t}^{BIC}}{ttlest_{g,t}}$$

ttlest^{BIC} = Total number of establishments in BIC i in year t in region g
ttlest = Total number of establishments in year t in region g

For each industry in the Broad Industry Category (BIC) in region *g*, and for each of the last two years available:

$$ttlSestqt_{g,t}^{BIC} = \frac{\left(\frac{Sest_{g,t}^{BIC}}{ttlest_{g,t}^{BIC}}\right)}{SQ_t^{BIC}} \times (P_{t,g}^{BIC})$$

Sest = Number of small establishments in region g and BIC i in year t
ttlest = Total number of establishments in region g and BIC i in year t

Note: if $ttlest_{g,t}^{BIC} = 0$, then we just consider the final value zero.

Then, we add up all values for all industries (there are a total of 10 BICs):

$$ttlSestqt_{g,t} = \sum_{BIC=1}^{10} ttlSestqt_{g,t}^{BIC}$$

Finally, we take the average of the last two years available:

$$ttlSestqt_g = \frac{ttlSestqt_{g,lya} + ttlSestqt_{g,lya-1}}{2}$$

Proprietorship

The U.S. Bureau of Economic Analysis (BEA) provides proprietorship data at the county-level, combining data for sole proprietorships and partnerships. A number of studies utilize BEA proprietorship data as it provides many years of data, which allows for time series analysis, and is available at the county-level.

Proprietorship Rate

Proprietorship rate measures the number of nonfarm proprietors relative to the total number of employed individuals, and gives an indication of how common self-employment is in a particular area. *Source: U.S. Bureau of Economic Analysis (BEA).*

$$prpr_g = \frac{\sum_{c=1}^{Ng} nfprp_{c,t}}{\sum_{c=1}^{Ng} ttlemp_{c,t}^{BEA}}$$

nfprp = Number of nonfarm proprietors

ttlemp = BEA total employment

Change in Proprietorship Rate

This measure shows the five-year change in proprietorship rate, 2007–2012: (These years were initially chosen because they mark the beginning and end of the Great Recession. In a sense, this is a measure of recovery.) In future updates of the index, the last five years of available data will be used. *Source: U.S. Bureau of Economic Analysis (BEA).*

$$prprd_g = \frac{\left(\frac{\sum_{c=1}^{Ng} nfprp_{c,lya}}{\sum_{c=1}^{Ng} ttlemp_{c,lya}^{BEA}} - \frac{\sum_{c=1}^{Ng} nfprp_{c,lya-5}}{\sum_{c=1}^{Ng} ttlemp_{c,lya-5}^{BEA}}\right)}{\frac{\sum_{c=1}^{Ng} nfprp_{c,lya-5}}{\sum_{c=1}^{Ng} ttlemp_{c,lya-5}^{BEA}}}$$

nfprp = Number of nonfarm proprietors
ttlemp = BEA total employment

Proprietor Income to Wages and Salaries Ratio

The proprietor income to wages and salaries ratio is measured at the county-level using values for proprietors' income, the number of proprietors, total wages and salaries, and the number of wage and salary employees. Proprietors' income includes all income from sole proprietorships, partnerships and tax-exempt cooperatives. County totals are aggregated to the regional level. *Source: U.S. Bureau of Economic Analysis (BEA).*

$$prpinc2WS_{g,t} = \frac{\left(\frac{\sum_{c=1}^{Ng} prpinc_{c,lya}}{\sum_{c=1}^{Ng} prpemp_{c,lya}}\right)}{\left(\frac{\sum_{c=1}^{Ng} WSinc_{c,lya}}{\sum_{c=1}^{Ng} WSemp_{c,lya}}\right)}$$

prpinc = Proprietors' income
prpemp = Number of proprietors
WSinc = Total wages and salaries
WSemp = Number of wage and salary employees

Availability of Capital from All Banks

The Federal Deposit Insurance Corporation (FDIC) conducts an annual survey of branch office deposits for all FDIC-insured institutions including U.S. branches of foreign banks. All institutions with branch offices are required to complete the survey. The survey results are available via the FDIC Summary of Deposits (SOD) database, which provides the total deposit amount for all branches and parent institutions. The state and county FIPS code associated with each branch location is provided. Only branches that are classified as either a full-service brick-and-mortar office or full-service retail office are included.

The local deposit share for all banks in the region is used as a proxy for local lending at the regional level. This measure takes the sum of all branch deposits within a specified area divided by the sum of the corresponding institution deposit totals. An institution total is included only once, regardless of whether the institution is represented by more than one branch. *Source: Federal Deposit Insurance Corporation (FDIC).*

$$lclcapttl_g = \frac{\sum_{b=1}^{Nb} depbr_{g,lya}^{b}}{\sum_{inst=1}^{Ni} depinst_{g,lya}^{inst}}$$

Nb = Total number of branches present in region g
Ni = Number of institutions with branches in region g
depbr = Branch office deposits
depinst = Total deposits of the institution

Employment and Productivity Index

Job Growth to Population Growth Ratio

This measure shows the change in BEA employment relative to the change in population from 2002 to the latest year available. Ideally, every county or region would have positive growth in both population and jobs; however, this is not the case. Many small rural counties have seen population declines. In order to account for regions that may experience population losses but employment gains, or vice versa, the formula needs to be able to reflect the relative dynamism of the local labor market. The formula uses the ratio of job growth to population growth (which may be negative), multiplies the ratio by the headcount change in the population (which may be negative) to get a scaled value that is then divided by the average of the population at both endpoints, a technique to estimate the average population over the period. The equation provides for the fact that a county or region may have growing employment but a declining population, which would be considered a positive outcome. *Source: U.S. Bureau of Economic Analysis (BEA) and U.S. Census Bureau Federal-State Cooperative for Population Estimates (FSCPE).*

First, calculate the job to population change ratio:

$$job2popratio_g = \frac{\left(\dfrac{ttlemp_{t=lya}^{BEA} - ttlemp_{t=2002}^{BEA}}{\dfrac{\left(tlemp_{t=lya}^{BEA} + ttlemp_{t=2002}^{BEA}\right)}{2}}\right)}{\left(\dfrac{pop_{t=lya}^{FSCPE} - pop_{t=2002}^{FSCPE}}{\dfrac{\left(pop_{t=lya}^{FSCPE} + pop_{t=2002}^{FSCPE}\right)}{2}}\right)}$$

Then, the population change headcount:

$$pop\_dhc_g = \left(pop_{t=lya}^{FSCPE} - pop_{t=2002}^{FSCPE}\right)$$

Finally, multiply *job2popratio* by *pop_dhc* and divide by the average of the two population endpoints:

$$job2pop_g = \ job2popratio_g \times pop\_dhc_g \ \div \ \left(\frac{pop_{t=lya}^{FSCPE} + pop_{t=2002}^{FSCPE}}{2}\right)$$

ttlemp: BEA total employment in year t
pop: FSCPE Population in region for year t

Change in Share of High-Tech Industry Employment

High-tech employment measures an aggregation of employment in key sectors (e.g., telecommunications, Internet providers, scientific laboratories). The industries considered high-tech are listed in **Table 9**. This measure is calculated as the average annual rate of change in the share of high-tech employment from 2002 to the latest year available. *Source: IBRC QCEW-complete employment estimates.*

$$HTempd_g = \frac{\ln\left(\frac{HTemp_{t=lya}}{ttlemp_{t=lya}^{QCEW}}\right) - \ln\left(\frac{HTemp_{t=2002}}{ttlemp_{t=2002}^{QCEW}}\right)}{lya - 2002}$$

HTemp: High-tech employment in year t in region
ttlemp: IBRC total employment in year t in region

Industry Performance

Industry performance includes three measures: cluster diversity, cluster strength and cluster growth. The cluster definitions and NAICS codes are described in Appendix B.

First, we remove all the clusters with trivial employment that may unduly affect growth rates. For all calculations below, we first calculate the sum of employment for the last two years available, in the region, by cluster. Then, we average the employment values and if it is less than 5, we consider that cluster as having no employment in the region. *Source: IBRC QCEW-complete employment estimates and Porter Cluster Mapping Project cluster definitions.*

$$\frac{\sum_{c=1}^{Ng}(emp_{c,lya}^{cl} + emp_{c,lya-1}^{cl})}{2} \geq 5$$

cl: cluster
emp_c^{cl}: IBRC employment in cluster cl in county c

Cluster Diversity

Cluster diversity is measured by the Shannon Evenness Index (SEI) using the Porter Cluster Mapping Project cluster aggregations of industries over the last two years available. A score of 1 indicates an even proportion of industries in a county/region. A score close to 0 indicates great concentration. The SEI for a region is divided by the national average SEI to create an index. The national SEI for 2013-2014 is 0.79.

First, for each cluster *cl* in region *g*, we calculate the proportion of employment for the last two years available:

$$p_{g,te}^{cl} = \frac{\sum_{c=1}^{Ng}(emp_{c,lya}^{cl} + emp_{c,lya-1}^{cl})}{\sum_{c=1}^{Ng}(ttlemp_{c,lya}^{QCEW} + ttlemp_{c,lya-1}^{QCEW})}$$

$ttlemp_c$ = IBRC QCEW total employment in county c
(this includes NAICS codes that do not fit in a cluster)
te = The two years at the end of the period, ie., lya and lya-1

The Shannon Evenness Index for *Ng* counties in region *g* is:

$$SEI_g = \frac{-\sum_{cl=1}^{n}[p_{g,te}^{cl} * \ln(p_{g,te}^{cl})]}{\ln(n)}$$

n = Number of clusters present (with average employment ≥5) in region g

The Shannon Evenness Index for the United States is:

$$SEI_{US} = \frac{-\sum_{cl=1}^{n_{US}}[p_{US,te}^{cl} * \ln(p_{US,te}^{cl})]}{\ln(n_{US})}$$

n_{US} = total number of clusters in the U.S.
$p^{cl}_{US,te}$ = Proportion of employment for cluster cl in the U.S. at time te

Finally, the cluster (or industrial) diversity index for region *g* is the ratio of the two SEI scores:

$$clstrdv_g = \frac{SEI_g}{SEI_{US}}$$

Cluster Strength

Cluster strength in a particular year is a modified location quotient (LQ) analysis that uses the number of clusters in a region to scale the sum of all LQs. Like an LQ, the proportion of employment in a cluster in a region is compared with the national proportion then summed across all clusters in region *g*.

The sum of LQs has little analytical power, but if divided by the number of clusters/industries/options/etc., the cluster strength measure, *$clstrstr_g$*, approaches 1 as the region becomes more diverse and similar to the nation as a whole and increases above 1 as clusters and their relative size become more dominant. Like LQs, the relative value for a particular cluster provides an indication of concentration for a cluster (or industry) relative to clusters in the region. The sum of LQs for the U.S. is equal to the number of clusters, namely, 71.

The first step in calculating region *g*'s cluster strength, $clstrstr_g$, is to calculate the cluster LQs for the last two years available, that is, to divide the cluster proportion component for a cluster in region *g* by the corresponding national value for cluster *cl*.

$$LQ_{g,te}^{cl} = \frac{p_{g,te}^{cl}}{p_{US,te}^{cl}}$$

cl = cluster
te = The two years at the end of the period, ie., lya and lya-1
p^{cl}_{te} *= Proportion of employment for cluster cl in time te*

Cluster strength in region g, $clstrStr_g$, is the sum of all of the individual cluster LQs in the region divided by the number of clusters present in the region.

$$clstrstr_g = \frac{\sum_{cl=1}^{n} LQ_{g,te}^{cl}}{n}$$

n: Number of clusters present (with average employment ≥5) in region g

It would be instructive for the regional performance analyst to know the leading clusters in a region. Because the complete array of LQs would be cumbersome, the website will show the top five (i.e., dominant) clusters for the region.

Cluster Growth Factor

Cluster growth measures the proportion of increase in regional employment that may be attributable to cluster employment growth. A rate of growth value does not discriminate between "metabolic" cluster growth (i.e., growth attributed to investment and resources internal to the region but open to technologies, human capital and knowledge developed from outside the region) and "magnetic" or "parachute growth" (new large-scale incoming investments and new establishments owned by firms from outside the region). In order to remove from analysis those clusters that grew metabolically, there is a criterion to help remove parachute jobs.

This technique attempts to identify a region's growth clusters (RGC), that is, the dominant clusters that are growing relative to the national average for those clusters. The cluster growth factor measure reports the percent of increase in regional employment that is attributable to regional growth clusters. It is a modified shift-share analysis for a 10-year time period that takes the ratio of the change in proportion of employment in cluster *cl* at the end and beginning of the time frame for region g. It compares the change in the region's cluster proportion with the U.S. ratio change for all non-zero employment clusters or non-missing clusters.[8] In other words, the change in share of employment in cluster *cl* for region *g* is divided by the change in share of employment in cluster *cl* for the United States.

First, we calculate a modified shift-share analysis for region *g* for the 10-year time period, defined as from *lya-9/lya-10* to *lya/lya-1*. The shift-share ratio for cluster *cl* in region *g*, $SS^{cl}{}_{g}$, takes the ratio of two-year averages of the proportion of employment in cluster *cl* at the end and beginning of the time period for region *g* and compares that ratio with the U.S. ratio for cluster *cl*. In other words, the share of employment in cluster *c* for region *g* is divided by the employment share in cluster *cl* for the U.S. This can be done by dividing the regional LQ for the cluster in the two years at the end of the time period by the LQ for the cluster at the beginning of the time period.

The shift-share ratio for cluster *cl* in region *g*, $SS^{cl}{}_{g}$:

$$SS^{cl}{}_{g} = \frac{LQ^{cl}_{g,te}}{LQ^{cl}_{g,tb}} = \frac{\frac{p^{cl}_{g,te}}{p^{cl}_{g,tb}}}{\frac{p^{cl}_{US,te}}{p^{cl}_{US,tb}}}$$

cl = Cluster
te = The two years at the end of the period, i.e., lya and lya-1
tb = The two years at the beginning of the period, i.e., lya-10 and lya-9
p^{cl} = Proportion of employment for cluster cl
$LQ^{c;}$ = Location quotient for cluster cl

Shift-share ratios greater than the change in overall employment for the U.S. would be considered provisional "regional growth clusters" (RGC). The set of RGCs is further reduced based on their size in the region. Small clusters or industries can experience wild changes in employment growth percentages because of their smaller base. Therefore, only clusters with an employment proportion, $p_g{}^{cl}$, greater than 0.005 of employment in the region are included.

[8] Keeping the zero/missing clusters distorts the standard deviation calculation.

In summary, there are four criteria for an RGC. These apply even for regions that experience a decline in overall employment:

1. The cluster has been growing, i.e., if the change in employment has been positive.
2. ${SS^{cl}}_g$ is greater than 1 (i.e., the cluster grew in relative importance).
3. ${SS^{cl}}_g$ is less than 1 plus two standard deviations of ${SS^{cl}}_g$ (this aims to remove the influence of parachute growth).
4. The proportion of employment in cluster *cl* during the time period *te* is greater than 0.005.

In an attempt to remove the parachute or magnetic growth phenomenon for any particular cluster, the upper limit to ${SS^{cl}}_g$ is the employment "parachute growth circuit breaker" (PGCB), which is: one (1) plus twice the standard deviation of the array of SS_g^{cl}. This keeps high-growth industries in the RGC category, while removing the most likely parachute establishments or firms. We use the population formula for the standard deviation as these are data from the population and not a sample.

$$PGCB_g = 1 + 2 * \left(\sqrt{\frac{\left(\sum_{cl=0}^{n} \left(SS_g^{cl} - \overline{SS_g} \right)^2 \right)}{n}} \right)$$

$\overline{SS_g}$ = The average shift-share ratio for region g

n = Number of clusters present (with average employment ≥5) in region g

The growth of dominant clusters—*clstrgrw*—is a percentage that represents the employment growth of RGCs compared to the total employment for the entire region. The growth of dominant clusters in region *g* is equal to the sum for all employment gains of the regional growth clusters (based on the four criteria) from the beginning of the period to the end divided by the average of total employment at the end of the period.

For clusters that meet all four criteria, their cluster growth factor, a percentage, is measured by:

$$clstrgrw_g = \frac{\sum_{rgc=1}^{Nrgc} \left({emp_{g,te}^{rgc}}/{2} - {emp_{g,tb}^{rgc}}/{2} \right)}{\left(\frac{\left(ttlemp_{g,te}^{QCEW} \right)}{2} \right)}$$

Nrgc = Number of RGCs in region g

$emp^{rgc}_{g,te}$ = IBRC QCEW employment in RGCs in region g and during time period te

$ttlemp_g$ = IBRC QCEW total employment in region g (this includes NAICS codes that do not fit in a cluster)

$clstrGrw_g$ can be interpreted as the percent of total employment that can be attributed to the regional growth clusters. The greater the percentage, the greater the role that RGC had in job growth. There is no obvious national value for $clstrGrw_g$ because at a national level, there is no regional cluster specialization. The percentage can be compared with other regions.

The core index for industry performance is the simple average of all three measures described above: diversity, cluster strength and the regional cluster growth.

Gross Domestic Product

GDP measures economic output at a point in time and change in GDP per worker measures increases in worker productivity.

Gross Domestic Product per Worker

The measure shows current-dollar GDP per employee in the latest year available. *Source: U.S. Bureau of Economic Analysis (BEA) and IBRC GDP-county-complete estimates.*

$$GDP2emp_g = \frac{\sum_{c=1}^{Ng} GDPcu_{c,t=lya}}{ttlemp_{g,t=lya}^{BEA}}$$

GDPcu = IBRC current-dollar GDP by county
ttlemp = BEA total employment in region

Change in Gross Domestic Product per Worker

This shows the annual rate of change in current-dollar GDP per employee from 2002 to the latest year available. *Source: U.S. Bureau of Economic Analysis (BEA) and IBRC GDP-county-complete estimates.*

$$GDP2empd_g = \frac{\ln\left(\frac{\sum_{c=1}^{Ng} GDPcu_{c,t=lya}}{ttlemp_{g,t=lya}^{BEA}}\right) - \ln\left(\frac{\sum_{c=1}^{Ng} GDPcu_{c,t=2002}}{ttlemp_{g,t=2002}^{BEA}}\right)}{lya - 2002}$$

GDPcu = IBRC current-dollar GDP by county
ttlemp = BEA total employment in region

Patents

Change in (Average) Patenting Rate

Version 1 of the Innovation Index used a measure of average utility patents per 1,000 workers. We have expanded this measure in this version to measure the change in (employment-scaled) patents over a 10-year period. In order to measure the change over time, we take a three-year total of employment at the beginning and the end of the time period and compare them. In other words, our final measure is something of a rate that compares patenting activity at the end of the period with activity at the beginning. This is calculated using the sum of patents and sum of employment over the last three years of the time frame divided by the sum of patents and sum of all employment in the first three years of a 10-year span. *Source: U.S. Patent and Trademark Office (USPTO).*

$$pat2empd_g = \left(\frac{\sum_{c=1}^{N_g}\sum_{lya-2}^{lya} ttlpat_{c,t}}{\sum_{c=1}^{N_g}\sum_{lya-2}^{lya} ttlemp_{c,t}^{BEA}/1{,}000}\right) \div \left(\frac{\sum_{c=1}^{N_g}\sum_{lya-10}^{lya-8} ttlpat_{c,t}}{\sum_{c=1}^{N_g}\sum_{lya-10}^{lya-8} ttlemp_{c,t}^{BEA}/1.000}\right)$$

ttlpat = Total patents issued
ttlemp = BEA total employment

Patent Diversity

Patent class diversity is measured using the Shannon Evenness Index for the last three years available. This measure compares the selected region to the U.S. diversity score to see if it holds a similar mix of patent categories as the nation. If the final score is above 1.00, the region is more diverse than the U.S. as a whole. *Source: U.S. Patent and Trademark Office (USPTO).*

For each utility patent in the last three years available, we match their *class* with the corresponding IBRC category listed in the **Table 6.**

For each region and every year of the last three years available, we calculate its Shannon index value ($SEIpat_{g,t}$):

$$SEIpat_{g,t} = \frac{\sum_{cat=1}^{N^{cat}} p_{g,t}^{cat} \ln(p_{g,t}^{cat})}{-\ln(N^{cat})}$$

$p^{cat}{}_g$= Proportion of total patents that are part of the IBRC category cat in region g (patcount/ttlpat)
N^{cat} = total number of IBRC categories (12)

We then average this value across the three years:

$$SEIpat_g = \frac{\sum_{t=lya-2}^{lya} SEIpat_{g,t}}{3}$$

Then, we calculate the same values for the U.S. as a whole during the same years:

$$SEIpat_{US,t} = \frac{\sum_{cat=1}^{N^{cat}} p_{US.t}^{cat}\, ln\left(p_{US,t}^{cat}\right)}{-\,ln(N^{cat})}$$

$P^{cat}{}_{US}$ = Proportion of total patents that are part of the IBRC category, cat, in the U.S.

$$SEIpat_{US} = \frac{\sum_{t=lya-2}^{lya} SEIpat_{US,t}}{3}$$

Finally, we compare the regional value with the national average for the last three years available:

$$patdv_g = SEIpat_g / SEIpat_{US}$$

Patents by Institution Type

There is interest in knowing the source of patents—i.e., federal government, non-government organization, individuals or foreigners. This metric will show descriptive statistics of the utility patents within a geographical region. *Source: U.S. Patent and Trademark Office (USPTO).*

The descriptive nature of this metric will simply report the results in five categories for the last six years available:

1. U.S. Individual
2. U.S. Non-Government Organization
3. U.S. Government
4. Foreign Source
5. Unassigned

Economic Well-Being Index

Per Capita Personal Income Growth

This measure of well-being is the average annual rate of change in per capita personal income from 2002 to the latest year available. *Source: U.S. Bureau of Economic Analysis (BEA).*

$$inc2popd_g = \frac{\ln\left(\frac{inc_{g,lya}}{pop_{g,lya}^{BEA}}\right) - \ln\left(\frac{inc_{g,2002}}{pop_{g,2002}^{BEA}}\right)}{lya - 2002}$$

inc = BEA personal income
pop = BEA population estimate

Compensation

Annual Wage and Salary Earnings per Worker Growth

This measure shows the average annual rate of change in wage and salary earnings per worker from 2002 to the latest year available. *Source: U.S. Bureau of Economic Analysis (BEA).*

$$WS2empd_g = \frac{\ln\left(\frac{WS_{g,lya}}{WSemp_{g,lya}}\right) - \ln\left(\frac{WS_{g,2002}}{WSemp_{g,2002}}\right)}{lya - 2002}$$

WS = BEA wage and salary earnings
WSemp = BEA wage and salary employees

Change in Proprietors' Income per Proprietor

This measure shows the average annual rate of change in proprietors' income per proprietor from 2002 to the latest year available. *Source: U.S. Bureau of Economic Analysis (BEA).*

$$prpinc2empd_g = \frac{\ln\left(\frac{prpinc_{g,lya}}{prpemp_{g,lya}}\right) - \ln\left(\frac{prpinc_{g,2002}}{prpemp_{g,2002}}\right)}{lya - 2002}$$

prpinc = BEA nonfarm proprietors' income
prpemp = BEA nonfarm proprietors employment

Income Inequality–Mean to Median Ratio

The regional income inequality ratio is calculated by summing county-level mean household income and dividing by the sum of county-level median household income, and then taking the inverse. *Source: U.S. Census Bureau American Community Survey (ACS).*

$$HHincdist_{g,lya} = 1 - \frac{\sum_{c=1}^{Ng}(HHincmean_{c,lya})}{\sum_{c=1}^{Ng}(HHincmdn_{c,lya})}$$

HHincmean = Mean household income
HHincmdn = Median household income

Average Poverty Rate

A high poverty rate is a negative outcome, so this measure, *abvpovr*, is one (1) minus the average poverty rate over the last three years available. *Source: U.S. Census Bureau American Community Survey (ACS).*

$$avgpovr_g = \frac{\sum_{t=lya-2}^{lya} pov_{g,t}}{\sum_{t=lya-2}^{lya} pop_{g,t}^{univ}}$$

pov = Number of impoverished persons
pop^{univ} = Population estimate for the poverty universe

$$abvpovr_g = (1 - avgpovr_g)$$

*abvpovr = The "positive" side of a poverty rate, that is, the rate of those **above** poverty*

Average Unemployment Rate

The unemployment rate is the number of persons seeking employment as a percentage of the total labor force. The reverse is the positive construct, the employment rate, empr. The last three years of the most recent unemployment rate data—the rate that is reported and tracked, for this series are used. *Source: U.S. Bureau of Labor Statistics (BLS).*

$$avgunempr_g = \frac{\sum_{t=lya-2}^{lya} unemp_{g,t}}{\sum_{t=lya-2}^{lya} ttlemp_{g,t}^{BLS}}$$

unemp = Number of unemployed persons
ttlemp = BLS number of persons in labor force

$$empr_g = (1 - avgunempr_g)$$

*empr = The "positive" side of an unemployment rate, that is, the rate of those **employed***

Dependency Ratio–Measured by Income Sources

To calculate the dependency ratio (non-earned income to personal income) for a particular region, we sum the county-level totals of personal transfer receipts and divide by the sum of county-level personal income totals, and then take the inverse. Personal transfer receipts include: Social Security and railroad retirement income; Supplemental Security Income; public assistance or welfare payments; and retirement, survivor and disability pensions. Personal income includes income from all sources: net earnings, dividend income, interest income, rent income and transfer receipts. *Source: U.S. Bureau of Economic Analysis (BEA).*

$$HHdpnd_g = 1 - \frac{\sum_{c=1}^{Ng}(HHtransrec_{c,lya})}{\sum_{c=1}^{Ng}(HHearnings_{c,lya} + HHincDIR_{c,lya} + HHtransrec_{c,lya})}$$

HHtransrec = Personal current transfer receipts
HHearnings = Net earnings
HHincDIR = Personal dividend, interest, and rent income

Average Net Migration

This measure is provided as net migration rate within the U.S. from 2009 to the latest year available. Net migration is the total number of a region's inbound migrants minus the total number of outbound migrants in the region for that year. It excludes inbound migration from other counties into the region. We sum the value of net migration for each county and then average it across the years. *Source: U.S. Census Bureau American Community Survey (ACS).*

$$netmigr_g = \frac{\sum_{t=2009}^{lya} netmig_{c,t}}{\sum_{t=2009}^{lya} pop_{g,t}^{ACS}}$$

netmig: Net domestic migration for year t to county c
pop: ACS Population for year t

State Context

Per Pupil Education Spending in K-12

Per pupil education spending data are measured at the state level and adjusted for regional cost differences using the National Center for Education Statistics (NCES) Geographic Cost of Education Index. This measure is taken directly from the National KIDS Count data set, a project of the Annie E. Casey Foundation.

Science and Engineering Graduates from State Institutions

This measure is the S&E graduates in the state (or states if a region crosses state boundaries) per 1,000 members of the population. *Source: U.S. Census Bureau and National Science Foundation (NSF).*

$$SEgrad2pop_{st} = \frac{SEgrad_{lya}}{Pop^{ACS}}$$

SEgrad= Number of science and engineering graduates—bachelor's and advanced degrees—for the latest year available
Pop = ACS population of the state in thousands for the latest year available

STEM Talent Flow

This measure is the proportion of STEM occupation in-migrants per 1,000 workers (at the state level). It is measured by the sum of all in migration STEM occupations divided by the total working-age population, defined as the entire population between the ages of 18 and 66. STEM occupations and their census and SOC codes are presented in Appendix B. *Source: U.S. Census Bureau American Community Survey (ACS).*

$$STEMmig2lab_{st} = \frac{\sum_{j=1}^{nj} STEMmig_{st,lya}^{j}}{lab_{st,lya}^{ACS}} \times 1{,}000$$

j = STEM occupation
nj = Number of STEM occupations in state st
STEMmig = Number of STEM in-migrants in state st
ttllab= ACS total working-age population, defined as the population between the ages of 18 and 66 in state st

Research and Development

There are seven measures in this section reflecting the variety in sources for funding and performers of R&D. *Source: National Science Foundation (NSF), U.S. Census Bureau and U.S. Bureau of Economic Analysis (BEA).*

Total R&D Expenditures as a Percentage of GDP

In order to take into account the size of the state economy, R&D spending is measured as a percentage of the state's current gross product. This is measured as total R&D performed by federal agencies, businesses, universities, other nonprofit organizations, and state agencies as a percent of gross domestic product of the state for that year. The value is averaged across the last three years available.

For each state and in the last three years available, we first calculate R&D as a percentage of GDP:

$$RD2GDP_{st,t} = \frac{RD_{st,t}}{GDP_{st,t}} \times 100$$

RD= Total research and development spending in year
GDP= Gross domestic product in state in year

Then, we calculate *avgRD2GDP*, total R&D spending as a percentage of GDP, averaged over three years:

$$avgRD2GDP_{st} = \frac{\sum_{t=lya-2}^{t=lya} RD2GDP_{st,t}}{3}$$

R&D Spending by Universities and Private Firms Per Capita

This measure incorporates the total spending by universities and private firms by state, or states if a region crosses state boundaries, per capita. It includes all research and development expenditures by universities and private firms for the last year available. The values are averaged across the last three years available.

For each state in the last three years available, we divide the R&D expenditures by universities and private firms by the total population in the state:

$$RDuprv2pop_{st,t} = \frac{RDuprv_{st,t}}{pop_{st,t}^{ACS}}$$

RDuprv = R&D expenditures by universities and private firms
pop = ACS population

Then, we calculate *avgRDuprv* as R&D spending by universities and private firms per capita averaged over three years:

$$avgRDuprv_{\ st} = \frac{\sum_{t=lya-2}^{t=lya} RDuprv2pop_{st,t}}{3}$$

Industry-Performed R&D as a Percentage of Industry Output

Industry-performed R&D is measured as a percent of industry output in order to take into account the size of the industry. This is the total R&D spending by businesses as a percentage of private industry output for each state and year. The final value is averaged across the last three years available.

For each state in the last three years available, we divide the industry-performed R&D by the total industry output:

$$RDind2out_{st,t} = \frac{RDind_{st,t}}{indout_{st,t}} \times 100$$

RDind = *Total industry-performed R&D*
indout = *Total industry output*

Then, we calculate *avgRDind* as the industry-performed R&D as a percent of industry output averaged over three years:

$$avgRDind_{st} = \frac{\sum_{t=lya-2}^{t=lya} RDind2out_{st,t}}{3}$$

Federal Expenditures for Academic and Nonprofit R&D Per Capita

This measure includes funds disbursed by all federal agencies toward R&D in universities, colleges and nonprofit organizations. The values are then scaled to the state population and averaged for the last three years available.

For each state in the last three years available, we divide federal expenditures for academic and nonprofit R&D by the total population in the state:

$$fedRDunfp2pop_{st,t} = \frac{fedRDunfp_{st,t}}{pop_{st,t}^{ACS}}$$

fedRDunfp = Federal R&D expenditures for academic and nonprofit
pop = ACS population in the state

Then, we calculate *avgfedRDunfp* as federal expenditures for academic and nonprofit R&D per capita averaged over three years:

$$avgfedRDunfp_{st} = \frac{\sum_{t=lya-2}^{t=lya} fedRDunfp2pop_{st,t}}{3}$$

University R&D Expenditures in Science and Engineering Per Capita

University funding of R&D in science and engineering is especially critical for predicting transfer of knowledge to the private sector and subsequent innovation. Indeed, these fields tend to produce research that is relevant to the industry.

This includes all university expenditures by state and by year toward research in science and engineering fields. The values are scaled by the state population then averaged across the last three years available.

For each state in the last three years available, we divide the total university R&D expenditures on science and engineering by the total population in the state:

$$RDuSE2pop_{st,t} = \frac{RDuSE_{st,t}}{Pop_{st,t}^{ACS}}$$

RDuSE = Total university R&D expenditures on science and engineering
pop= ACS population in the state

Then, we calculate *avgRDuSE* as the total university R&D expenditures on science and engineering per capita averaged across three years:

$$avgRDuSE_{st} = \frac{\sum_{t=lya-2}^{t=lya} RDuSE2pop_{st,t}}{3}$$

Industry Funding of Academic Research Per Capita

Industry funding of academic research measures all university expenditures by state and year that were financed by businesses. The values are scaled to the state population and then averaged across the last three years available.

For each state in the last three years available, we divide the industry funding of academic research by the total population in the state:

$$indRDu2pop_{st,t} = \frac{indRDu_{st,t}}{pop_{st,t}^{ACS}}$$

indRDu = Industry funding of academic research
pop = ACS population in the state

Then, we calculate *avgindRDu* as the industry funding of academic research per capita averaged across three years:

$$avgindRDu_{st} = \frac{\sum_{t=lya-2}^{t=lya} indRDu2pop_{st,t}}{3}$$

State Funding of Academic Research Per Capita

This measure includes all university expenditures by state and year that were financed by either the state or local governments. The values are scaled to the state population and then averaged across the last three years available.

For each state in the last three years available, we divide the state and local government funding of academic research by the total population in the state:

$$stRDu2pop_{st,t} = \frac{stRDu_{st.t}}{pop_{st,t}^{ACs}}$$

stRDu = State and local government funding of academic research
pop = ACS population in the state

Then, we calculate *avgstRDu* as the state and local government funding of academic research per capita averaged across three years:

$$avgstRDu_{st} = \frac{\sum_{t=lya-2}^{t=lya} stRDu2pop_{st,t}}{3}$$

Institutionally-Based Startups

Sup2RD measures the startups formed and headquartered in the home state relative to total R&D expenditures as a three-year average. *Source: The Association of University Technology Managers, AUTM Licensing Survey.*

$$Sup2RD_{st} = \frac{\sum_{t=lya-2}^{lya}\left(\sum_{i=1}^{ni} \frac{Sup_{st,t}{}^{i}}{RD_{st,t}{}^{i}}\right)}{3}$$

i = Institution
ni = Number of institutions in state st
Sup = Number of in-state startups formed
RD = AUTM total institution R&D expenditures

Small Business Innovation Research and Technology Transfer Awards

Research has shown that SBIR/STTR grants tend to be clustered in larger cities, which intuitively makes sense due to the localities having more resources as well as more economic activity. Therefore, instead of measuring SBIR/STTR grants by establishment sizes, we created a per capita SBIR/STTR measure. Recognizing that the SBIR/STTR grants are for very early-stage developments, we used a long time series. *Source: Small Business Administration (SBIR/STTR) and U.S. Census Bureau Federal-State Cooperative for Population Estimates (FSCPE).*

$$Sba_{st} = \frac{\sum_{t=2002}^{lya} \$value_{st,t}}{\sum_{t=2002}^{lya} pop_{st,t}^{FSCPE}}$$

$value = SBIR/STTR grant dollars
pop = FSCPE Census population

Kauffman Entrepreneurship Index

The Kauffman Index of Entrepreneurial Activity represents the percentage of people ages 20 to 64 who do not own a business in the first survey month that start a business in the following survey month. *Source: Kauffman Foundation.*

Only new business owners who report working a minimum of 15 hours per week on their own business and do not work more hours at a wage or salary job are included in the Kauffman count of new entrepreneurs.

The Kauffman Foundation codes as "1" a person who starts a business in month 2 of being surveyed. The percentage of new business owners is the sum of the number of "1" (one) observations divided by the total number of survey observations. This measure aligns with the Kaufman index of entrepreneurial activity.

$$Kfm_{st} = \frac{Kfment_{st,t}}{Kfmpop_{st,t}}$$

Kfment = Number of new business owners in second survey month who work a minimum of 15 hours on their own business and do not work more hours for a wage or salary job
Kf_pop = Number of survey respondents

Business Formation and Survival

Establishment Entry Rate

This measure is a three-year average of the establishment entry rate (i.e., the percent of total establishments that are less than one year old). *Source: U.S. Bureau of Labor Statistics Business Employment Dynamics.*

$$estfrm_{st} = \frac{\sum_{t=lya-2}^{lya}\left(\frac{estnew_{st,t}}{ttlest_{st,t}}\right)}{3}$$

estnew = Number of establishments less than one year old
ttlest = Total number of establishments

Establishment Survival Rate

This measure is a three-year average of the one-year survival rate (i.e., the percent of total establishments born in the first year that exist the following year). *Source: U.S. Bureau of Labor Statistics Business Employment Dynamics.*

$$estsrvr_{st} = \frac{\sum_{t=lya-2}^{lya}\left(\frac{estsrv_{st,t}}{estnew_{st,t}}\right)}{3}$$

estsrv = Number of establishments less than one year old in the first year that still existed in the second year

estnew = Number of establishments less than one year old in the first year

Volunteer Rate

This measure uses data from the latest year available, which is reported as a three-year average. There is no need to adjust the raw data, so it is used directly from the source.
Source: Volunteering and Civic Life in America Survey, Corporation for National and Community Service.

Appendix B: Cluster Definitions

Several additional reference tables are helpful to those seeking to understand the data used within the Innovation Index. These are too lengthy to include within this report, so we are making them available online.

The full list of occupation cluster definitions is available at www.statsamerica.org/ii2/reports/OccupationClusters.xlsx.

The full list of industry cluster definitions is available at www.statsamerica.org/ii2/reports/PorterClusters.xlsx.