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Lessons From *Patchwork Nation*: A New Framework for Building Community Indicators

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Keywords: Community indicators, principal components analysis, data democratization, community health needs assessment, data visualization

Key Points

- As interest in outcomes continues to rise, community indicators have become a widely used tool to measure progress. While indicators provide a vehicle for understanding and addressing community issues from a holistic perspective, current efforts seem to suffer from both a notable absence of local-level data and end-user information overload, whereby the presentation of numerous and often disconnected indicators makes it difficult to draw meaningful conclusions from the analysis.
- We highlight the results and our experiences with a community health needs assessment conducted through an indicator project in Michigan's Kent County. The analysis and visualization of the indicator project was based on the book *Our Patchwork Nation: The Surprising Truth About the 'Real' America* and the website PatchworkNation.org. Using principal components analysis, we reduced a set of 25 separate indicators developed through broad participation into a five-component solution at the census-tract level to facilitate greater understanding of health needs and disparities across the county. The result is a more informative approach to assessing community needs that is easily understandable, visually appealing, and more applicable to a broad audience.
- We believe the lessons learned from our approach to community-indicator projects can help other grantmakers increase the effectiveness of data-intensive, large-scale community-indicator work.

Introduction

Measuring impact has become increasingly important in philanthropy as foundations seek to learn more about the impact of their investments by measuring the achievements of the programs and projects they support. In an era where demand seems only to increase and resources will always be limited, identifying needs and priorities must be the foundation of any philanthropic endeavor. As the nonprofit sector has grown in size and scale over the past 30 years, so has the pressure on nonprofits that deliver health and human services to operate efficiently. To reduce administrative costs and put more dollars into services, community indicators are increasingly becoming part of assessing need.

This article attempts to provide an approach that enhances the usefulness of community-indicator projects. We build upon the work of previous community-indicator scholars while employing a similar methodological approach – principal components analysis (PCA) – used in the work *Our Patchwork Nation: The Surprising Truth About the Real America* (Chinni & Gimple, 2010). The result is a more informative approach to assessing community needs that is easily understandable, visually appealing, and more applicable to a broad audience. We believe the lessons learned from our approach to community-indicator projects can help other grantmakers increase the effectiveness of data-intensive, large-scale community-indicator work.

First, we provide an overview of the rationale that drove our approach. This is followed by a brief overview of the literature related to recent critiques of community-indicator work; the critique of the current practice in community indicators is highlighted in the context of nascent data-democratization efforts. We then apply PCA to the multitude of community indicators developed as part of a community health needs assessment for Kent County, Michigan.

False Dichotomy

Pundits often point to the near ubiquitous “Republican red” and “Democratic blue” map of America’s counties as way of highlighting our nation’s political leanings. Closer inspection, however, is warranted. Chinni and Gimple (2010) expose the problems associated with this false dichotomy.

Raised in the Detroit suburb of Warren, Chinni writes of being particularly vexed by the “blue” labeling of Michigan’s Wayne and Washtenaw counties – counties with striking differences. Wayne County is home to Detroit. In 2010 Wayne’s median income was \$40,590 and per capita income was \$21,405; the overall poverty rate was 22.5 percent and the child poverty rate was 32.6 percent (U.S. Census Bureau, 2007 - 2010e). The proportion of the population with a bachelor’s degree was just 20.4 percent (U.S. Census Bureau, 2007 - 2010f). Washtenaw County, home to Ann Arbor and the University of Michigan, is about 40 miles west of Detroit. The median income in Washtenaw was \$56,708 in 2010, per capita income was \$30,594, and the overall poverty and child poverty rates were just 13.7 percent (U.S. Census Bureau, 2007 - 2010c). The proportion of Washtenaw’s population with a bachelor’s degree or greater was 50.6 percent, more than twice that of Wayne (U.S. Census Bureau, 2007 - 2010d).

How could Wayne County and Detroit, synonymous with urban decay, and Washtenaw County and Ann Arbor, often listed among the top places in to live in the U.S., be thought of as “similar” because they are “blue”? This question prompted a move beyond the broad generalization of “red”

Community indicators are a system of measures designed, developed, and analyzed by community members to provide neighborhood-level information for community-building and policymaking. Indicators are seen as increasingly important measures, providing policymakers with information to address essential questions related to health and well-being of the overall population as well as for certain subgroups.

and “blue” designations toward a new paradigm – a more nuanced approach that more accurately characterizes the diversity of the United States by classifying each of America’s 3,141 counties into one of 12 community types.¹

Community Indicators: A Brief History

Community indicators are a system of measures designed, developed, and analyzed by community members to provide neighborhood-level information for community-building and policymaking (National Neighborhood Indicators Partnership, 2012; Smolko, Strange, & Venetoulis, 2006). Indicators are seen as increasingly important measures, providing policymakers with information to address essential questions related to health and well-being of the overall population as well as for certain subgroups, including age (e.g. children, seniors) and race/ethnicity (e.g. African American, Hispanic) (Ben-Arieh & Goerge, 2001).

¹ Much of Chinni and Gimple’s work can be found online at www.patchworknation.org

As a consequence, communities seeking to develop indicator projects are often overwhelmed by the information produced from such efforts, leading to poor results that fail to deliver the clear outcomes required for incorporation into decision-making.

The practice of measuring and tracking populations is a long one despite some disagreement among scholars as to precisely when indicators were introduced. Scholars taking a broader view contend that population-based health measures found as early as the 1600s established the field. In some circles, the London “Bills of Mortality” are considered among the first indicators; they contained information on the number of deaths associated with the plague through recordings of the names and parishes of the dead (Johnson, 2006). Mortality rates, derived from death certificates, are commonly used today to compare the relative health of populations (Institute of Medicine, 2008). Those who define the indicator movement more narrowly contend the field is not quite a century old. In the United States, President Herbert Hoover established the Committee on Social Trends in 1929 (Zill, Sigal, & Brim, 1983), resulting in the first reports on child well-being in the 1940s (Ben-Arieh, 2006).

Enthusiasm for community indicators has ebbed and flowed in the past 50 years, with the modern indicator movement traced to UNICEF’s State of the World’s Children annual report (Ben-Arieh, 2008). Most recently there has been a large increase in indicator work and projects; since the early 1990s more than 200 separate indicator projects have been identified in the United States alone (Smolko et al., 2006). In addition, the field now has at least two peer-reviewed journals dedi-

cated to the discipline: *Social Indicators Review* and *Child Indicators Research*.

Despite the interest in community indicators, researchers continue to find many efforts plagued with problems that defeat their utility, such as weak methodology and poor conceptualization. The problems appear most acute at local levels. For example, there remains an absence of well-established theories to guide the selection of indicators and a lack of appropriate data in the spatial scales that are of greatest interest to most policymakers (Wong, 2002). Innes and Booher (2000) and Sawicki (2002) note that many community-indicator projects often result in the development of literally hundreds of indicators. As a consequence, communities seeking to develop indicator projects are often overwhelmed by the information produced from such efforts, leading to poor results that fail to deliver the clear outcomes required for incorporation into decision-making (Gahin, Veleva, & Hart, 2003; Innes & Booher, 2000; Sawicki, 2002).

There are, however, differing recommendations for those building community indicators. Innes and Booher tend to favor building consensus among facilitators, stressing the importance of community engagement that brings community leaders to a shared vision for the project. Sawicki, on the other hand, advocates an approach based on a rational-paradigm model, emphasizing the role of the science while employing methodologically sound strategies in creating potential indicators. Even when methodologically sound, however, many indicator initiatives are wasted because the information derived from them are not incorporated into programmatic decisions (Holden, 2009; Memon & Johnstone, 2008). While Holden (2009) attributes the problem primarily to a dearth of research in the area, Memon and Johnstone (2008) point to shortcomings in conceptual design.

As more communities recognize the potential for data-driven decision-making, Thomas Kingsley of the Urban Institute warns that the massive amounts of data that are increasingly available for community-indicator projects are no silver

bullet (2011). In a new era where data will play an increasingly important role in community development, harnessing the full potential of data democratization remains an elusive goal. Although logic might dictate that ever more specialized technological knowledge and analysis will be required to fully unlock the power of big data, Kingsley argues that skill deficits are not the barriers that many believe. Rather, he contends that the key challenge will be in delivering information to practitioners in simple, readily understandable formats.

Data Democratization

Data democratization refers to a combination of policy and technology innovations that make government and other administrative data available to anyone with a computer and access to the Internet. This phenomenon is occurring in three ways: 1) a general broadening of access to data across the country, 2) a reduction in the skill level required to turn data into useful information for policy initiatives, and 3) the driving of analysis and decision-making to more localized entities and populations (Sawicki & Craig, 1996).

President Obama campaigned on the idea of open government and the democratization of data, launching Data.gov – making economic, health, environmental, and other government data available from a single website. These and other powerful forces have aligned, potentially empowering community-based groups with the information to make policy decisions that will improve the health and well-being of their communities.

Data democratization and technological advances do not fully explain the increasing interest in data-driven decision making. A number of broad national interests, such as the environment and, more recently, measuring social trends and the notion of community well-being, continue to raise interest in community-indicator work (Phillips, 2003). This trend is also likely exacerbated by devolution that continues to drive decision-making and provision of services to lower levels of government. Over the past 20 years, nonprofits, often largely supported through philanthropy, have been offering a greater share of essential

health and human services in response to government decentralization and devolution (Suárez & Lee, 2011). In 2011, U.S. foundations gave \$46.9 billion, up from just \$30.5 billion a decade earlier. Even adjusting for inflation, foundation giving increased by approximately \$5 billion in that period (Lawrence, 2012).

The combination of technological advances and devolution provides opportunities for citizens to engage in community-indicator projects, and the success of such initiatives depends on active community involvement (Memon & Johnstone, 2008; Phillips, 2003; Zachary, Brutschy, West, Keenan, & Stevens, 2010).

Methodology

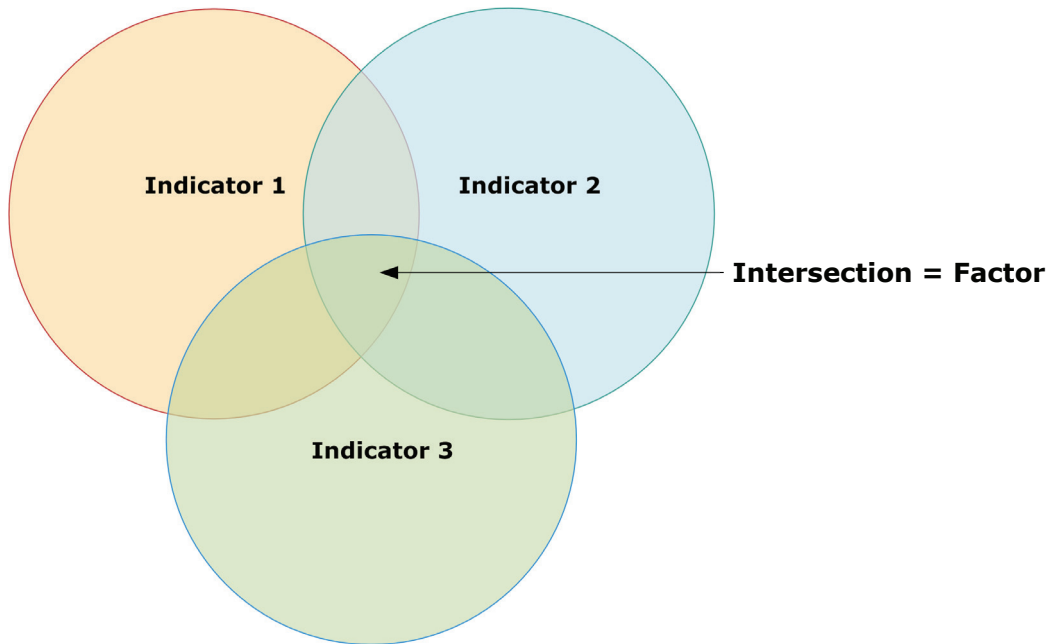
The sweeping reforms of the Patient Protection and Affordable Care Act (ACA), also known as “Obamacare,” is forcing health care providers to take a closer look at the health of their communities. While most politicians and media have focused on the seminal achievement of the legislation – market reforms and the expansion of health insurance – the act contains numerous lesser-known provisions. In particular, it links public health and clinical care by imposing new requirements on tax-exempt hospitals, requiring a Community Health Needs Assessment at least once every three years (Patient Protection and Affordable Care Act, 2010).

In the fall 2012 semester, the students in Political Science 310 – an upper-level undergraduate health-policy course at Grand Valley State University – set out to think about the overall health of Kent County, Michigan, in a new way. The semester-long class project was based on the principles of *Patchwork Nation*, culminating in the Community Health Score (www.communityhealthscore.org), an effort to assess the health needs of each of Kent County’s 128 communities using publicly available data sources.

Communities as Units of Analysis

The influences of *Patchwork Nation* on the project were many, but two were especially significant. First, in pointing out the obvious flaws of the red county/blue county system as a description

FIGURE 1 Principal Components Analysis Conceptual Model



From Chinni & Gimple, *Our Patchwork Nation: The Surprising Truth About the Real America*. Copyright © 2010 by Gotham Books, a member of Penguin Group (USA), Inc. Reprinted by permission of Penguin Group, Inc.

of American politics, Chinni and Gimple’s work reinforced the view that the unit of analysis (e.g. the whom, what, and level of geography of the study) must be driven to lower and more practical levels. Because children and their families often live in communities that are the explicit targets of philanthropy-funded interventions, it is important to understand in a more nuanced way Kent County’s communities and their potential needs. Communities, therefore, can serve as the unit of analysis or measurement when assessing the overall well-being of residents.

Highly aggregated data do not provide a clear understanding of the well-being of Kent County residents. Chinni and Gimple point out that regions, states, and Metropolitan Statistical Areas were simply too large to provide useful information. Applying similar logic, the students challenged themselves to better define the concept of “community.”

Kent County contains the educational, demographic, and income disparities found between Wayne and Washtenaw counties. Grand Rapids, Kent County’s largest city, has a population of about 188,000 (U.S. Census Bureau, 2007 - 2010a). The median household income in 2010 was \$38,731 and the city’s overall poverty rate was 25.5 percent (U.S. Census Bureau, 2007 - 2010b). Ada, a small township east of Grand Rapids, has a population slightly more than 13,000 (U.S. Census Bureau, 2007 - 2010a). Median household income there in 2010 was \$103,526 and the overall poverty rate was just 3.1 percent (U.S. Census Bureau, 2007 - 2010b). Although nonwhite populations continue to grow in West Michigan, whites remain a majority in Grand Rapids, comprising 64.4 percent of the population. Ada is 93.3 percent white (U.S. Census Bureau, 2007 - 2010a).

Although Chinni and Gimple settled on the county as their unit of analysis, the census tract

became the unit of analysis for Kent because of the need for a more granular approach to examine differences in the county. Census tracts are small, relatively permanent geographic entities within counties (or the statistical equivalents of counties) delineated by a committee of local data users. Generally, census tracts have between 2,500 and 8,000 residents and boundaries that follow visible features. When established, census tracts are to be as homogeneous as possible with respect to population characteristics, economic status, and living conditions (Economics and Statistics Administration & Bureau of the Census, 1994). There are 128 census tracts in Kent County.

Principal Components Analysis

The second key influence of Patchwork Nation was in shaping the statistical analysis and visualization of the results. The students employed a statistical procedure called principal components analysis (PCA), a type of factor analysis frequently used as a data-reduction technique (DeCoster, 1998) and more recently in data-mining (SAS Institute Inc., 2011). Frequently used for conceptual clarity and simplification, PCA tests data for clusters or patterns within multiple variables that can be difficult to detect otherwise. This analysis permits the researcher to pare the list of variables by reducing the number of dimensions, yet without great loss of information.

This is a critical point as data-democratization efforts expand the potential for creating ever more individual indicators, which can ultimately overwhelm the users of the information. For example, the existence of clusters suggests that a group of variables may be measuring aspects of the same dimension, also known as factors. By reducing the data set from a group of interrelated variables to a smaller set of uncorrelated factors, PCA explains the greatest variance with the smallest number of explanatory concepts (Field, 2000). In practice, it is a commonly employed method among researchers analyzing survey results, especially when measuring complex attitudes, behaviors, or personality traits, which are better measured through an inventory of questions rather than a single one (Chinni & Gimble, 2010; Field, 2000).

PCA works through a mathematical process that seeks to cluster variables in a meaningful way, by capturing the extent of the overlap in each of the indicators through evaluating the interrelationships. (See Figure 1.) Where the overlap occurs, the indicators are grouped to produce a single underlying component or factor. Data reduction is achieved as groupings are discovered among the indicators that highly correlate with one another (Chinni & Gimble, 2010; Field, 2000). This technique allowed the students to take an extensive set of indicators and reduce them to five components present at their foundation.

Indicator Development

Students began selecting potential indicators of community health around three domains: access to care, socioeconomic factors, and physical and environmental factors. Indicator selection was largely patterned after the *County Health Rankings & Roadmaps* program, created by the University of Wisconsin Population Health Institute.² This comprehensive approach forced the students to consider the notion of community health beyond more than the actual system of health care delivery to include social determinants of health: social, economic, physical, and environmental influences. The U.S. Centers for Disease Control and Prevention defines social determinants of health as the circumstances in which people are born, grow up, live, work, and age, as well as the systems in place to deal with illness. These circumstances are in turn shaped by a wider set of forces: economics, social policies, and politics (Centers for Disease Control and Prevention, 2012).

To develop potential ideal indicators to measure the overall health of a community in Kent County, the criteria for selection were based on the extent to which the indicator was:

- supported in peer-reviewed literature (an established link between the indicator and health outcomes),
- well-defined (clear and purposeful),

² A detailed methodology and results of the rankings can be found at www.countyhealthrankings.org

Table 1 Indicator by Domain and Data Source

Indicator (Practical Measure)	Data Source
Access to Health Care Indicators	
<ul style="list-style-type: none"> • Percentage of women receiving less than adequate prenatal care as measured by the Kotelchuck Index (access to prenatal care) • Percentage of households without a vehicle • Percentage of adults with less than a high school degree (proxy for health insurance) • Percent of adults with a bachelor's degree or higher (proxy for health insurance) • Percentage of seniors (62+) living alone (proxy for isolation) • Percentage of population that speaks English "less than well" (language barriers) 	<p style="text-align: center;">Michigan Department of Community Health Vital Statistics</p> <p style="text-align: center;">U.S. Census Bureau</p>
Socioeconomic Indicators	
<ul style="list-style-type: none"> • Percentage of single-female-headed households with children under 18 • Percentage of households receiving benefits through Supplemental Nutritional Assistance Program (food stamps) • Percentage of population receiving public assistance (welfare benefits) • Percentage of households with seniors (62+) • Median household income • Per capita income • Percentage of population living in poverty • Percentage of children living in poverty • Average household size • Average family size • Percentage of population that is nonwhite 	<p style="text-align: center;">U.S. Census Bureau</p>
Physical and Environmental Indicators	
<ul style="list-style-type: none"> • Population density (proxy for urban and rural) • Percentage of working population with commutes longer than 45 minutes each way (sedentary lifestyle) • Percentage of population living within 1 mile of a fast-food restaurant (poor eating habits) • Percentage of population living within 1 mile of a supermarket (access to healthy food) 	<p style="text-align: center;">U.S. Census Bureau</p> <p style="text-align: center;">Derived from U.S. Business Listings (Supermarket and Fast-Food Restaurants)</p>

- valid and reliable (consistently measures what it is supposed to measure),
- easily understood (by the people who need to act on information),
- responsive to trends (relatively quickly and noticeably),
- feasible (to measure, either directly or by proxy),
- comparable (consistent with local, state, and national measures),
- available and timely (available and affordable data sources, collected at least annually), and
- assignable to the community (community = census tract).

Data to construct the indicators were selected from a wide range of administrative data sets, including the U.S. Census Bureau, Michigan Department of Community Health Vital Records, and ESRI Business Analyst.

Results

The students developed more than 50 potential individual indicators. For each indicator, they adopted a common approach to ensure reporting consistency across how each indicator was measured, the rationale for why it was chosen, data analysis, and the source of the data. Not all indicators conformed to the selection parameters, primarily because of data availability. For example, public health data for proposed indicators on such topics as fruit and vegetable consumption, alcohol use, and smoking exist only at the county level. In other instances, potentially interesting data from the American Community Survey, administered by the U.S. Census Bureau, had missing values or unacceptably high margins of error. Although there are a number of acceptable strategies for imputing missing values, the students decided to exclude indicators with missing values in such instances. They decided exclusion of these variables would have no meaningful impact on the analysis since most of the missing data and high sampling errors were confined to small subsets of the population, such as children between the ages of 3 and 4 enrolled in preschool.

Although the students retained almost 40 acceptable indicators, the final model included only 25

separate indicators that were available at a sufficiently detailed level, were the appropriate unit of analysis, and contributed to the overall model accuracy. (See Table 1.) Each of those 25 indicators is clustered within one domain, but it is clear that many indicators could arguably fall within more than one of the three domains. The organization of the indicators by domain has no impact on PCA. The domains were established merely to help the student work groups think about health in a broader sense in order to develop a more comprehensive list of potential indicators to better assess the health of the communities in Kent County.

As a result of the analysis, PCA reduced the broad set indicators into five components or factors. (See Table 2.) This factor-component matrix depicts the correlations between each community's characteristics for the respective indicator and the five components, also known as the factor loadings. For example, the correlation between the percentage of households with no vehicle and Component 1 is 0.957. Correlations can range between -1 and 1, with the sign depending on the nature of the relationship. Therefore, the relationship between the percentage of households with no vehicle and Component 1 is both positive and very strong.

Note that in Table 2, a number of the correlation coefficients are in boldface type. For example, in the Component 1 column the correlations or factor loadings are emphasized in boldface type because they are much higher than the loadings in the same column for each of the other four components. This is because loadings below 0.4 or 0.3 (depending on researcher preference) irrespective of the sign (+ or -) are ignored because of the weak association (Field, 2000). Although factor scores are generated for all variables, the students used a more conservative cutoff of 0.4 to ensure that only the variables with the strongest association for each factor remained part of the final solution.

Reducing the broad set of indicators into a more manageable five-component solution provides a more nuanced understanding of the community need.

Table 2 Principal Components Analysis Scores

Indicator	Component				
	1	2	3	4	5
Percentage of households without car	.957	-.239	.011	.173	.042
Percentage receiving public assistance	.891	.168	-.030	.049	.013
Percentage receiving SSI	.886	-.017	-.065	.058	-.054
Population living in poverty	.812	-.008	.048	-.118	-.015
Percentage of households receiving SNAP	.791	.165	.008	-.178	-.147
Percentage of children living in poverty	.735	.035	.062	-.616	-.088
Percentage of single-female-headed households with children	.611	.282	.106	-.158	.057
Percentage of nonwhite population	.563	.329	.282	-.186	.062
Percentage of mothers receiving less than adequate prenatal care	.545	.061	.189	-.251	-.088
Average household size	-.027	.950	-.071	.052	.101
Average family size	.136	.892	.061	-.025	-.014
Percentage of married couples with children	-.376	.705	.196	.346	-.057
Percentage of population that speaks English "less than well"	.227	.585	.173	-.276	-.046
Percentage of adults with less than high school degree	.404	.445	.052	-.417	-.036
Percentage of working population that commutes longer than 45 minutes each way	.164	.050	-.755	-.322	-.030
Percentage of population within 1 mile of fast-food restaurant	.057	-.124	.723	-.320	-.068
Percentage of population within 1 mile of healthy food	.120	.119	.717	-.159	-.033
Population density per square mile	.199	.053	.712	-.128	-.144
Median home value	.117	-.025	-.165	.943	-.050
Percentage of adults with bachelor's degree or higher	.007	-.042	.225	.930	.089
Per capita income	-.065	-.032	-.055	.882	.047
Median household income	-.323	.305	-.097	.709	-.010
Percentage of births to teen mothers	.417	-.033	.062	-.416	-.175
Percentage of households with seniors (62+) living alone	.125	-.077	.092	-.062	.979
Percent of households with seniors (62+)	-.107	.105	-.134	-.025	.923

Each of the components is grouped by the common characteristics they tend to exhibit. After reviewing the PCA solution, the students developed the names and descriptions for each component or community in Kent County:

1. *Decidedly Disadvantaged.* Clearly the most vulnerable communities. These communities have poor access to appropriate prenatal care and their households are the most likely to be without a vehicle. Primarily urban communi-

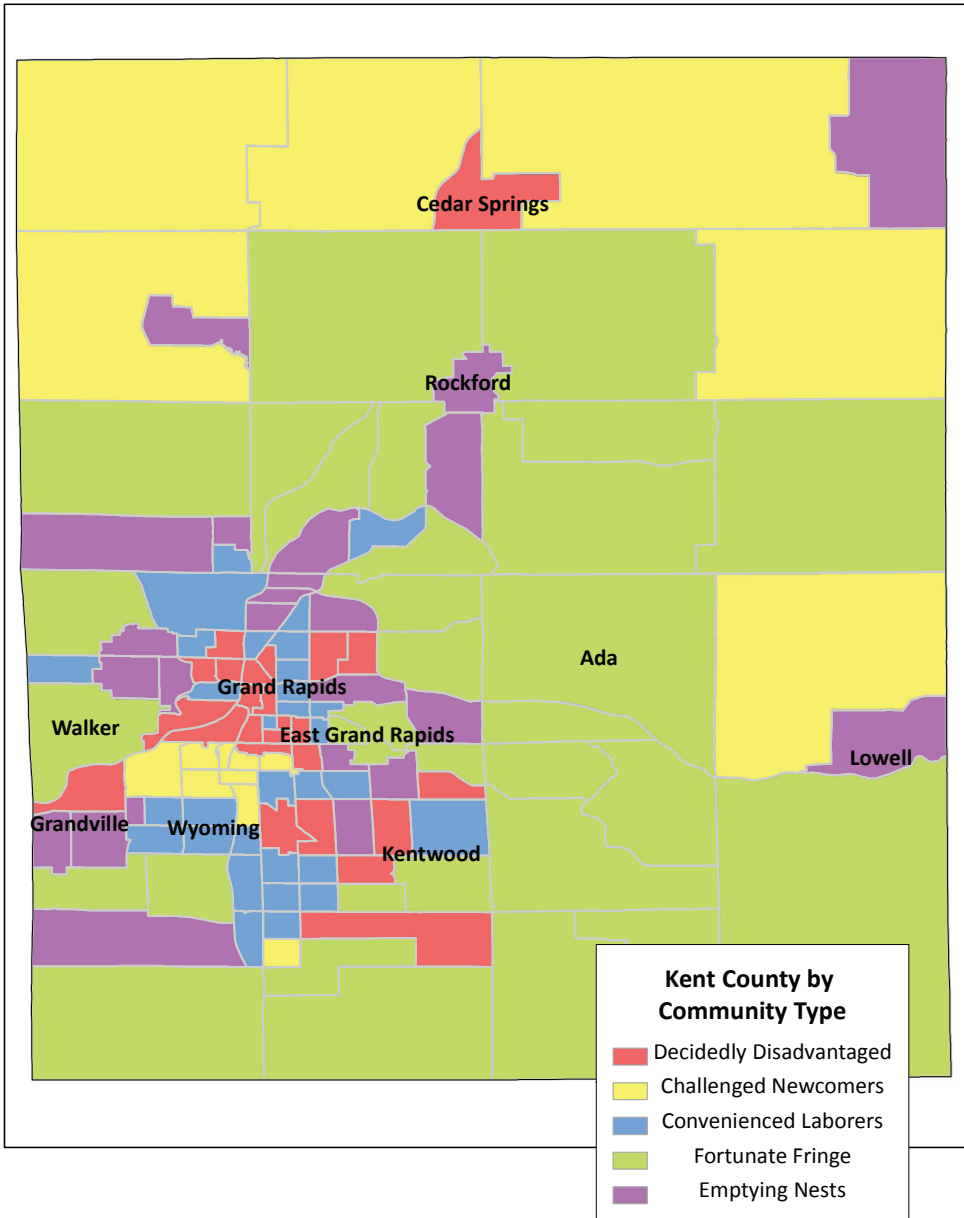
ties, the Decidedly Disadvantaged have better access to fast-food restaurants than to healthy food at a traditional supermarket.

2. *Challenged Newcomers.* The youngest communities. The median age in Challenged Newcomer communities – 31.8 years – is nearly 3 years under the median age of Kent County, which is 34.5 years. Although predominantly white, these communities have the highest proportion of Latinos. Nearly half of all households have children under age 18 and more than an eighth of the population has difficulty communicating in English. Challenged Newcomer communities have the highest rates of births to mothers without a high school degree. Among those that commute to work, they have the highest proportion of those spending 45 minutes or more each way in a car.
3. *Convenienced Laborer.* Most easily characterized as lower-middle class. The racial/ethnic makeup of these communities is quite similar to Kent County overall. Although these communities have the highest labor-force participation rates in Kent County, the majority living in these communities most likely do not have well-paying jobs – as evidenced by the relatively low per capita income, low rates of college attainment, and rates of food-stamp use higher than the county average. These communities are perhaps most characterized by their proximity to both healthy food via their suburban nature and to fast-food restaurants.
4. *Fortunate Fringe.* The most affluent communities. Largely suburban and overwhelmingly white, they are the least racially and ethnically diverse among the five community types. Per capita and median incomes are much higher for the Fortunate Fringe, which is not surprising given the high levels of the education and low levels of single-female-headed households.
5. *Emptying Nests.* Communities with large swaths of aging baby boomers, where grown

children have moved away from home. The median age of these communities is more than 4 years higher than Kent County as a whole and nearly 10 years higher than the Decidedly Disadvantaged. Emptying Nests are more likely to have households with senior citizens and the least likely to have children under 18; about 15 percent of households are comprised of seniors living alone.

After developing the typology, the students assigned to each community a single, best-fitting type for the visualization component of the project. (See Figure 2.) Each community received a score to rank the strength of association between the respective community and each of the five components or typologies. Typically, communities that ranked highest on a single specific component were assigned to that component. In some cases, communities ranked high on more than one component; this is often the result of indicators that load highly on more than one component. For example, the proportion of the population age 25 and up with less than a high school degree indicator loaded high on Component 1 (Decidedly Disadvantaged) and Component 2 (Challenged Newcomers). That indicates that while the pattern of loadings is strong, there is some complexity between these two groups than cannot be explained solely by the proportion of the population without a high school degree. This accounts for the final model, explaining 82.7 percent of the variance between the communities. In simple terms, this means that slightly more than 17 percent of the differences between the communities cannot be explained by the indicators in the model; there are other factors at work. Unfortunately, there is no statistical procedure or definitive rule to appropriately assign the communities in such instances. Therefore, these communities were examined case by case and assigned to the most appropriate component based on the students' familiarity with Kent County. The result is a map that distills the 25 indicators developed for each of the county's 128 communities into more revealing and interpretable patterns – the five community types.

FIGURE 2 Kent County Communities by Type



Discussion

The forces of data democratization, technological advances, devolution, and greater accountability for scarce resources seem unlikely to abate in the foreseeable future. Big data is likely to get bigger, making it increasingly more challenging to make sense of a cornucopia of information. Data from

such sources as the Local Employment Dynamics, Census 2010, and the American Community Survey will have a significant impact not only at the national and regional level, but locally. Managed well, these data can provide fresh insights into communities. While there are any number of approaches to community-indicator work, PCA

combined with good data-visualization techniques is worthy of consideration as an appropriate methodological choice involving multiple indicators that often measure, whether knowingly or not, the same dimensions.

The Lessons of *Patchwork Nation*

Principal components analysis, developed over a century ago by Karl Pearson (Pearson, 1901), has a long history. Although PCA is most often used in the fields of biology and psychology, the technique has also been applied in other social-indicator and community-index projects. In fact, a search of the terms “principal components analysis” and “community indicators” in the journal *Social Indicators Research* returned 394 articles.³ In addition, a recent, thorough methodological piece by Vyas and Kumaranayake (2006) dedicated to appropriate application of PCA when working with indicators would be helpful to anyone considering the approach. Furthermore, *Patchwork Nation* is not even the first study of its kind. Richard Florida’s seminal work, *The Rise of the Creative Class* (2002, 2012), is methodologically similar, but explores the occupational, demographic, psychological, and economic characteristics shared by people who are making their cities exciting and dynamic places to live.

That being said, the key contribution of *Patchwork Nation* to the field of indicator research is the PCA approach that made possible the thoughtful descriptions and the captivating visualization of the results. This breakthrough satisfies Kingsley’s standard of simplicity. Consider Figure 2, which represents each of Kent County’s community types. That single map portrays some 3,200 numbers – 128 communities with 25 separate indicators each. As Edward Tufte, the pioneer in the visual display of information and a proponent of data maps, says of maps, “Only a picture can carry such a volume of data in such a small space” (2001, p. 16). Combined with well-crafted, thoughtful descriptions of the community types, good visualization can move consumers of indicator projects to the substantive content of work instead of bogging them down in techniques

or methodology. Furthermore, data reduction as a result of PCA provides the opportunity to present the results in a way that drawing conclusions from dozens of separate indicators cannot.

Because many community-indicator projects are developed for broad-based consumption, it is critical to move consumers of this information toward more useful purposes. If they can find meaning in the results, the findings can be incorporated into programmatic decisions that address problems at the community level and thereby make use of philanthropic support. As data become more available, grantmakers and communities will find little use for simple univariate descriptions of the data and will demand that indicator efforts be part of the search for solutions to critical community issues.

In addition to the Community Health Score project, the students engaged in a community-indicator project in 2010 that employed PCA. This approach was conducive to working with community members whose input shaped the indicator selection for the Great Start Collaborative (GSC) of Kent County. The collaborative is a community-based, comprehensive system of programs aimed at fostering school readiness and life success for children up to age 5. A diverse group of community participants, working in four groups of about a dozen each, generated about 30 indicators for the project. Broad participation, while necessary for participant and community buy-in, resulted in a large number of indicators that often measured similar dimensions of childhood need but were nonetheless different indicators. The PCA methodology permitted the inclusion of most of the indicators that the work groups developed, avoiding the alienation among participants that resulted from earlier efforts when their input was cut from the analysis as redundant or otherwise unnecessary. PCA allowed the students to keep nearly all of the variables proposed by the work groups in a final three-component solution.

Perhaps most important, PCA gave GSC new insights into early childhood services. Before the project, Grand Rapids, western Michigan’s largest city, had tended to dominate discussions of need.

³ Online search conducted July 24, 2013.

Including both spatial and categorical components in the project made clear the abundance of need outside of the urban center of the county (as Figure 2 demonstrates in the Community Health Score project). A greater understanding of the diversity of Kent County's communities made it clear that, like the needs uncovered in the Community Health Score project, no single policy or strategy can address all the county's early childhood needs. Ultimately, the Chinni and Gimple framework enabled the students to distill massive amounts of data into manageable information, leading to a more appropriate focus on and discussion of the issues.

While the approach taken in *Patchwork Nation*, and PCA in particular, may be useful in community-indicator projects, they are not without limitations. They are best suited for needs assessments or establishing baselines from which to compare interventions, and should not be mistaken for program evaluation. Furthermore, there is a clear subjective component to PCA, especially where communities loaded highly on more than one component. A Decidedly Disadvantaged may share some of the characteristics of a Challenged Newcomers or Fortunate Fringe community. Furthermore, Fortunate Fringe communities are not without problems even though they suffer from fewer health disparities or needs. Such analysis can help identify areas within broader geographies where limited resources are likely to have the greatest impact.

Lastly, the availability of data – although admittedly imperfect – at localized levels is becoming a game changer for grantmakers and community partners. Quantitative community data offer only one perspective on community strengths and needs. Another perspective comes from the voices of those within those communities. Information from multiple sources, including qualitative measures, may be the best way to verify data and ensure a more complete data-driven process.

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