City-Level Measures of Health, Health Determinants, and Equity to Foster Population Health Improvement: The City Health Dashboard

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Objectives. To support efforts to improve urban population health, we created a City Health Dashboard with area-specific data on health status, determinants of health, and equity at city and subcity (census tract) levels.

Methods. We developed a Web-based resource that includes 37 metrics across 5 domains: social and economic factors, physical environment, health behaviors, health outcomes, and clinical care. For the largest 500 US cities, the Dashboard presents metrics calculated to the city level and, where possible, subcity level from multiple data sources, including national health surveys, vital statistics, federal administrative data, and state education data sets.

Results. Iterative input from city partners shaped Dashboard development, ensuring that measures can be compared across user-selected cities and linked to evidence-based policies to spur action. Reports from early deployment indicate that the Dashboard fills an important need for city- and subcity-level data, fostering more granular understanding of health and its drivers and supporting associated priority-setting.

Conclusions. By providing accessible city-level data on health and its determinants, the City Health Dashboard complements local surveillance efforts and supports urban population health improvement on a national scale. (*Am J Public Health.* 2019;109:585–592. doi:10.2105/AJPH.2018.304903)

As the proportion of the US population living in urban areas (>80% in 2010) continues to grow, policies and programs that advance the health of city residents are increasingly central to achieving national goals to improve population health.[1] To propel improvements in urban population health and health equity, reliable measures of health and health determinants at the city and neighborhood level are essential. Currently, however, a major data gap regarding urban health indicators impedes health improvement efforts: although data on health and its drivers are routinely reported at the county and state level, city-level reporting is far less consistent, often leaving city-level managers and local communities without accurate data on their jurisdictions and neighborhoods.

Durable population-wide improvements in health and health equity require the active engagement not only of health care and public health but of other sectors as well.[2] Initiatives like the County Health Rankings and Roadmaps have helped advance widespread understanding of drivers responsible for better health and health equity by reporting health-related data from diverse sectors at the county level.[3] Most US cities, however, are not contiguous with county boundaries: of the 500 largest US cities, 16% bridge more than 1 county, and most others constitute only a relatively small portion of a county's population (~30%, on average).[4] County data are thus insufficient for many municipal leaders seeking to initiate health improvement initiatives in their jurisdictions. Although the health departments of some large cities have robust surveillance and analytic capabilities, most local health departments do not.

Several recent initiatives have begun to make important inroads in providing city-level data, focusing principally on health behaviors (500 Cities) or on large cities with more advanced analytic capabilities (Big Cities Health Coalition).[5,6] Still lacking, however, is a broadly accessible resource that presents a uniform set of city and subcity measures of health status, health determinants, and health equity similarly calculated for all US cities of a certain size to allow for "apples-to-apples" comparisons between cities. To address this gap, acting with foundation support, we developed the City Health Dashboard as a national resource for the largest 500 US cities.

METHODS

A cornerstone approach in developing the City Health Dashboard has been collaboration with its intended audience of city-level policymakers and community leaders. Cultivation of city stakeholder input was facilitated by 3 "bridging partner" organizations with extensive city-level relationships: the National Resource Network, the National League of Cities, and the International City and County Managers' Association. Teams

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This article was accepted November 24, 2018.
doi: 10.2105/AJPH.2018.304903

identified from 4 early partner cities (Waco, TX, Kansas City, KS, Flint, MI, and Providence, RI), typically including representatives of the mayor's office, the health department or equivalent, and local community health coalitions, hosted site visits by the project team and joined development calls, deeply informing the development process with their understanding of cities' and communities' health-related data needs and priorities. Following development of a prototype for the new resource, representatives drawn from a broader group of 15 cities of diverse sizes, compositions, and geographic locations helped guide its refinement.

City Selection

We aligned our city selection to match that of the 500 Cities Project of the Centers for Disease Control and Prevention (CDC). Using the 2010 Census, the 500 Cities Project identified the 500 most populated US cities, constituting 33% of the US population. To ensure national representation, we followed the CDC in replacing the smallest 3 cities on the list with the largest city in West Virginia, Wyoming, and Vermont, states otherwise not represented.[5] Excluding the cities from these 3 states, the population of the cities in our sample ranged from 66 102 to 8 175 133.

Measure Selection

We sought to define a parsimonious set of actionable measures of health, health determinants, and health equity that could be derived from national data sets to apply to the city level and, where possible, to census tracts within cities.

Inclusion criteria. Inclusion criteria, defined with city partners, called for measures that (1) were derived from national-level data sets with rigorous methodological underpinnings, sufficiently granular to permit city-level calculation, and accessible to our team, ensuring comparability across locations and avoiding the need for primary data collection; (2) addressed prespecified domains of health and determinants (next paragraph); (3) were important to and could be actionable by city- and community-level stakeholders; and (4) were updated regularly, preferably annually.

Candidate measures. We compiled a master list of over 100 potential measures to consider, drawing in part on a wide range of recent and current compendia of measures of population health and health determinants.[7–11] We assigned candidate measures to 1 of 5 overarching domains: social and economic factors, physical environment, health behaviors, health outcomes, and clinical care. After eliminating measures that did not meet inclusion criteria, we further winnowed the list with city stakeholder groups to ensure alignment with decision-makers' needs, and with an external advisory board of experts in urban health measurement and improvement. Ultimately, we selected 37 measures apportioned across the 5 domains (Table 1).

Data Sources and Measure Calculation

Eleven distinct national data sets were the source of 35 measures, and we used state-level data sets for 2 educational measures (Table 1). We established data use agreements with parent entities, and we stored data securely on local servers. None included personal health information. We imported data sets into SAS version 9.4 (SAS Institute, Cary, NC) for analysis.

We used census designations to define city boundaries.[12] Census tract was the primary unit for subcity analysis because criteria for defining these geographies are consistent nationally. Of the 37 measures, 22 are presented at the census tract level. We calculated confidence intervals at the 90% level following Census Bureau recommendations for all measures except indices and education measures.[13,14]

In the following paragraphs, descriptions of measure calculations are organized by source of the underlying data set.

Behavioral Risk Factor Surveillance System: 500 Cities project. Ten Dashboard measures were estimates derived by the CDC using Behavioral Risk Factor Surveillance System (BRFSS) data for the 500 Cities project and shared with us for inclusion in the City Health Dashboard. These measures span the domains of health outcomes (5 measures), health behaviors (3 measures), and clinical care (2 measures; Table 1). For the 2018 release, the CDC generally calculated these model-based estimates using 2015 and 2016 BRFSS data and census block–level demographic information.[15,16]

American Community Survey. We used publicly available American Community Survey (ACS) data to calculate 6 social and economic measures, 2 measures of the physical environment, and 1 clinical care measure (Table 1). We downloaded data from American FactFinder for the years 2012 to 2016 for each city at 2 geographic levels: city ("census-designated place") and census tract.

For 3 measures (children in poverty, unemployment, and uninsured), data at the city level were also available by race/ethnicity. We reported these data at the census tract level and city-wide by demographic group, using the following racial/ethnic categories: White, non-Hispanic; African American or Black; Asian (including Native Hawaiian or Pacific Islander); Hispanic; and other (including American Indian/Alaska Native, multiracial, and other). Unemployment and uninsured data were also available by gender, and uninsured data were additionally available by age.

We applied methods developed by the Washington State Department of Health for the 2 physical environment measures derived from ACS data: housing with potential lead risk and lead exposure risk index. The first represents the percentage of housing that poses lead exposure risk based on year of construction. Because low-income households are more vulnerable to elevated blood lead levels,[17] the second measure combines housing age and population living in poverty into an index ranging from 1 to 10, with 10 representing the highest risk of lead poisoning.[18]

National Vital Statistics System. We calculated (to the city level) restricted-use National Vital Statistics System (NVSS) data for 2014 to 2016, performed on-site at the National Center for Health Statistics (NCHS) Research Data Center in Hyattsville, Maryland. We derived 8 Dashboard measures (5 mortality and 3 natality measures) from these data (Table 1). City-level NVSS measures used population denominators accessed from the ACS (5-year estimates for 2011–2015), except low-birth-weight births and adequate prenatal care, which are both expressed as a percentage of all live births. To calculate NVSS measures by race/ethnicity, we used county-level population denominators from the NCHS Vintage 2016 Bridged-Race Postcensal Population Estimates data file for 2015. Race/ethnic-specific estimates are presented at the county level, except in limited circumstances where city boundaries

TABLE 1—Measures Included in the City Health Dashboard and Their Characteristics: United States

Measure	Data Source	Count (C) vs Modeled Estimate (E)	Subcity Estimates	Race/ Ethnicity Estimates	Year(s) of Data Collection	Similar Measure Used in County Health Rankings & Roadmaps
Health outcomes domain						
Premature deaths (all causes) (YPLL-75)	NVSS	C	No	No	2014–2016	Yes
Frequent physical distress	500 Cities	E	Yes	No	2016, 2-y modeled estimates	Yes
Frequent mental distress	500 Cities	E	Yes	No	2016, 2-y modeled estimates	Yes
Low birth weight	NVSS	C	No	Yes	2014–2016	Yes
Obesity	500 Cities	E	Yes	No	2016, 2-y modeled estimates	Yes
High blood pressure	500 Cities	E	Yes	No	2015, 2-y modeled estimates	No
Diabetes	500 Cities	E	Yes	No	2016, 2-y modeled estimates	Yes
Cardiovascular disease deaths	NVSS	C	No	Yes	2014–2016	No
Colorectal cancer deaths	NVSS	C	No	Yes	2014–2016	No
Breast cancer deaths (females only)	NVSS	C	No	Yes	2014–2016	No
Opioid overdose deaths	NVSS	C	No	No	2014–2016	Yes
Life expectancy	USALEEP	E	Yes	No	2010–2015, 6-y modeled estimates	No
Health behaviors domain						
Binge drinking	500 Cities	E	Yes	No	2016, 2-y modeled estimates	Yes
Smoking	500 Cities	E	Yes	No	2016, 2-y modeled estimates	Yes
Physical inactivity	500 Cities	E	Yes	No	2016, 2-y modeled estimates	Yes
Adolescent births	NVSS	C	No	Yes	2014–2016	Yes
Clinical care domain						
Primary care physicians	AMA Masterfile	C	No	No	2018	Yes
Dental care	500 Cities	E	Yes	No	2016, 2-y modeled estimates	Yes
Uninsured	ACS	C	Yes	Yes	2016, 5-y estimate	Yes
Preventive services	500 Cities	E	Yes	No	2016, 2-y modeled estimates	No
Prenatal care	NVSS	C	No	Yes	2014–2016	No
Social and economic factors domain						
High school graduation	State data	C	No	Yes	Year varies by state	Yes
Third-grade reading proficiency	State data	C	No	No	Year varies by state	No
Absenteeism	USDOE	C	No	Yes	2015–2016	No
Unemployment	ACS	C	Yes	Yes	2016, 5-y estimate	Yes
Children in poverty	ACS	C	Yes	Yes	2016, 5-y estimate	Yes
Income inequality	ACS	C	Yes	No	2016, 5-y estimate	Yes
Housing cost, excessive	ACS	C	Yes	No	2016, 5-y estimate	Yes
Racial/ethnic diversity	ACS	C	Yes	No	2016, 5-y estimate	No
Neighborhood racial/ethnic segregation	ACS	C	Yes	No	2016, 5-y estimate	Yes
Violent crime	UCR	C	No	No	2017	Yes
Physical environment domain						
Walkability	Walk Score	E	Yes		2018	No
Air pollution—particulate matter	EPA	E	Yes		2013, 1-y estimate	Yes

Continued

TABLE 1—*Continued*

Measure	Data Source	Count (C) vs Modeled Estimate (E)	Subcity Estimates	Race/ Ethnicity Estimates	Year(s) of Data Collection	Similar Measure Used in County Health Rankings & Roadmaps
			Health outcomes domain			
Housing with potential lead risk	ACS	C	Yes	No	2016, 5-y estimate	No
Lead exposure risk index	ACS	C	Yes	No	2016, 5-y estimate	No
Limited access to healthy foods	USDA	E	Yes	Yes	2015 estimates	Yes
Park access	ParkServe	E	No	Yes	2017	Yes

Note. ACS = American Community Survey; AMA = American Medical Association; EPA = US Environmental Protection Agency; NVSS = National Vital Statistics System; UCR = Uniform Crime Reporting Program; USALEEP = US Small-Area Life Expectancy Estimates Project; USDA = US Department of Agriculture; USDOE = US Department of Education; YPLL-75 = years of potential life lost at age 75 years. County Health Rankings & Roadmaps comparison current as of February, 2019.

were contiguous with, larger than, or crossed county boundaries.[14]

We calculated years of potential life lost at age 75 years (YPLL-75) by methods described in the literature.[19] We calculated opioid-related mortality using *International Classification of Diseases, 10th Revision* (*ICD-10*) codes X40 to X44, X60 to X64, X85, Y10 to Y14, T40.0 to T40.4, and T40.6 in the multiple cause of death field.[20] We calculated cardiovascular disease mortality using *ICD-10* codes modified from Nolte and McKee[21]; we calculated breast cancer mortality in females using *ICD-10* codes C500 to C504, C506, C508, and C509[22]; we defined colorectal cancer mortality by *ICD-10* codes C180 to C189, C19, and C20.[23] We age-adjusted YPLL-75 and other mortality rates and expressed them as a rate per 100 000. We defined adolescent births as births to mothers aged 15 to 19 years and calculated them as a rate per 1000 females aged 15 to 19 years. We estimated adequate prenatal care as the percentage of live births for which prenatal care was initiated in the first trimester. We calculated low-birth-weight births as the percentage of live births for which birth weight was less than 2500 grams.

Per NCHS guidelines, for all vital statistics measures, we set the numerator threshold at 10, below which we censored estimates.[24] We also set a denominator threshold of 50. All vital statistics measures except opioid-related mortality were calculable by race/ethnicity; YPLL-75, colorectal cancer mortality, and cardiovascular disease mortality were also calculable by gender.

Other national data sets. A measure of life expectancy at birth for all US census tracts was developed by the National Association for Public Health Statistics and Information Systems, the NCHS, and the Robert Wood Johnson Foundation for the US Small-Area Life Expectancy Estimates Project (USALEEP). This modeled summary measure is based on the number of deaths and age at death of residents (aggregated into 5-year intervals) in each census tract during the years 2010 to 2015.[25]

Air pollution–particulate matter estimates were modeled by the US Environmental Protection Agency's Community Multiscale Air Quality Modeling System for all census tracts in the contiguous United States for 2013.[26] We calculated annual averages of fine particulate matter (≤ 2.5 μg in diameter) from the reported daily values.

To represent food access, we used census tract–level estimates for 2015 produced by the US Department of Agriculture Economic Research Service's Food Access Research Atlas of the population living half a mile or further from a supermarket, large grocery store, or supercenter.[27] Estimates were calculable for demographic subgroups at the city level.

Walkability, an attribute of the built environment, is presented as an index calculated by Walk Score, representing a community's ability to access a range of amenities on foot.[28]

Violent crime data, provided by the Federal Bureau of Investigation's Uniform Crime Reporting program, report counts of homicide, aggravated assault, forcible rape, and robbery in 2015, normalized as an annual rate per 100 000 population.[29]

We used American Medical Association Physician Masterfile data to represent the count of licensed MDs and DOs in primary care specialties (family practice, general practice, internal medicine, and pediatrics) in clinical practice in 2018, normalized per 100 000 population.[30]

We accessed data on chronic absenteeism, defined as a student missing 15 or more days of instruction, via the US Department of Education's 2015–2016 Civil Rights Data Collection survey.[31]

Park access is presented as the percentage of the population in a given area living within a 10-minute walk of green space, as calculated by ParkServe.[32]

State-based education data sources. We downloaded publicly available data on third-grade reading proficiency and high school graduation rates for each state's most current year of data (generally the 2015–2016 school year) from state departments of education. Third-grade reading proficiency is defined as the percentage of third-graders who score "proficient" or higher on state-based tests of academic readiness. Although tests vary by state, they share the objective of identifying grade readiness in reading skills. The denominator is the sum of third-grade students who completed the standardized examination. We calculated high school graduation rate as the percentage of high school seniors who graduated within 4 years of entering ninth grade. Data on these 2 education measures were available at the city level, including by race/ethnicity and gender for high school graduation.

Addressing health equity. We employed 2 approaches to incorporate a health equity focus across the Dashboard: data disaggregation and direct measures. Where possible, we included data disaggregated by geography, gender, and race/ethnicity for Dashboard measures (Table 1). Additionally, we included 3 direct measures relevant to health equity, each derived from ACS 5-year estimates for 2012 to 2016: the Index of Concentration at the Extremes (ICE),[33] racial/ethnic diversity, and neighborhood racial/ethnic segregation.[34] ICE provides both quantitative and qualitative information on the distribution of resources in a community. Its value ranges from (–)1.0 to (+)1.0, with the lowest and highest values indicating that all residents live in households in the lowest or highest income quintiles of the US household income distribution, respectively, and a value of 0 signifying an equal distribution of households across upper and lower quintiles, or that no households fall into upper or lower quintiles.

Building on the work of Iceland et al.,[34] we used related measures for racial/ethnic diversity and neighborhood racial/ethnic segregation. Racial/ethnic diversity (also known as the Entropy Score) represents the heterogeneity of racial/ethnic groups in a census tract or city on a scale of 0 to 100. A value of 0 indicates that all residents of the area belong to a single racial/ethnic category; a value of 100 indicates that all racial/ethnic groups present are evenly represented. Neighborhood racial/ethnic segregation (also known as the Entropy Index or Theil's H) represents the extent to which the racial/ethnic composition of a census tract differs from that of the surrounding city. Neighborhood racial/ethnic segregation is also represented on a scale from 0 to 100, but here, lower values are preferable. If the racial/ethnic composition of a city's census tracts tends to be more homogenous than that of the city overall, the segregation index would be closer to 100.

Web Site Development

We developed a Web-based platform with iterative input from city stakeholders; it includes map-style visual displays, tables, benchmarking against national averages, features enabling comparisons across cities, and visual correlation displays between 2 measures at the neighborhood level (e.g., obesity and walkability). During a 2-month beta-testing period, municipal partners suggested many improvements that were subsequently incorporated into the site's layout, features, and narration.

RESULTS

A prototype version of the Dashboard, developed for the 4 early partner cities and released in January 2017, provided initial proof of concept. Six months following the prototype site's launch, we asked stakeholders from the 4 cities for specific examples of uptake and use. A sample of these use cases is presented in Table 2. In addition, we made numerous improvements to the site's design and functionality in response to feedback from city stakeholders, including clarification of visual displays, tools for ascertaining census tract–level correlation between 2 measures, and downloadable data files.

In May 2018, we publicly launched the full City Health Dashboard site, with data for 500 US cities (www.cityhealthdashboard.com). Webinars, press releases, and outreach by the bridging partner organizations fostered awareness of and opportunities to use the new resource among a wide range of municipal and community stakeholders. Numerous local officials and community leaders have remarked on the value of having access for the first time to integrated measures of health status, health determinants, and equity specific to their city's geographic boundaries (and, where available, census tract boundaries). In the first 8 months following launch, there were more than 47 000 unique users of the site. Many organizations with a regional or topical public health- or policy-oriented focus have expressed strong interest in the new resource as well.

DISCUSSION

As the US population continues to concentrate in cities, municipal policies are ever more important to health and well-being. Underscoring this is a growing recognition that population health is the product of diverse determinants, of which many—early childhood education, affordable housing, and ready opportunities for physical activity—are shaped at the city level. We developed the City Health Dashboard to remedy the current lack of access to data on the health of urban populations and to provide a practical tool to support city policymakers and communities in undertaking population health assessment and improvement initiatives. With more granular measures of health status, health determinants, and health equity available in a single uniform platform, local stakeholders can access the data needed to establish and address priorities and identify approaches that improve both population health and health equity. Early indications from the 4 early partner cities suggest that the Dashboard is meeting important needs, through insights from data not previously "visible" to neighborhood planners, anticipated reductions in the burden of future Community Health Needs Assessments, and performance comparisons against "peer" cities.

Other resources are emerging for city and community stakeholder use in assessing municipal population health, each with unique strengths. Most notably, the 500 Cities initiative launched by the CDC includes additional BRFSS measures of health behavior, health status, and care received, leveraging recent advances in small-area analytics. This important effort has for the first time illuminated specific within-city (and between-city) variations for many health indicators. Although the City Health Dashboard incorporates some but not all of the 500 Cities metrics, it places them in a broader context of other actionable measures of health status and health determinants, including important socioeconomic characteristics. The Big Cities Health Coalition offers city-level data for the 30 largest US cities. Although an outstanding resource for these municipalities, it does not reach hundreds of small and midsize cities with often minimal resources for public health measurement. The County Health Rankings and Roadmaps, which has played a vital role in fostering national awareness of health's social determinants, portrays city-level data only when municipal and county boundaries are coterminous. The Healthiest Communities rankings recently issued by *US News & World Report* and the Aetna Foundation also focus on county-level indicators. Most other publically available resources do not include measures purposefully coded to city geographies. A further strength of the City Health Dashboard is its user-centered design. Responding to

TABLE 2—City Health Dashboard: Use Case Examples From Early Partner Cities

Project Phase	Use Case	Comments
Providence, RI		
Implementation	Neighborhood opportunities for physical activity: The City of Providence's Healthy Communities Office (HCO) identified South Providence as a priority area for increasing physical activity. Dashboard data revealed that, despite high walkability scores, residents of this area reported low levels of physical activity and high levels of obesity. This insight prompted the HCO to focus on identifying barriers and opportunities for increased walking, biking, and other active transportation. They are now triangulating Dashboard data with other quantitative sources, as well as a community-based participatory research process, to gain further insight into the mismatch between walkability and physical activity and to better understand potential drivers of activity in South Providence. New information gathered will be used to ensure that city efforts to promote walking and biking are in fact aligned with community need.	Stimulated supplementation of quantitative data with local qualitative data. Prompted integration of local with state and federal data for more comprehensive analysis. Strengthened justification for funding allocation.
Waco, TX		
Implementation	Improving access to care for the underserved: Waco's Access to Care Working Group has been using community health workers (CHWs) to help meet medical needs of underserved residents. CHWs are assigned to specific neighborhoods and, although they responded to constituents' expressed needs, they lacked data to set specific priorities for training, education, and targeted intervention. By accessing the Dashboard's neighborhood-level data, CHWs were able to determine which specific health and social concerns were more prevalent in their particular catchment areas and subsequently focus training on addressing these areas. They are now poised to provide more effectively targeted services to their residents.	Neighborhood-level data on many key measures were previously not available to community-engaged stakeholders. Allowed for priority-driven targeting of time and resources.
Kansas City, KS		
Site development	Metrics that meet city needs: Kansas City officials took full advantage of the process of determining which metrics would be included on the Dashboard. Engaging community members through a participatory process to determine which health and social issues were most salient to residents, they ensured that the final measures selected addressed community priorities while also meeting city policymakers' needs. The Kansas Health Institute, a key local stakeholder actively engaged in the site's development, indicated interest in having its grantees use Dashboard data in conducting needs assessments in support of their applications.	Participatory process had benefits to cities that included community engagement regarding health priorities. Offered new resource to support health-related grant making.
Future use	Fostering "apples-to-apples" comparisons: Because Kansas City and Wyandotte County boundaries are nearly coterminous, the County Health Rankings and Roadmaps are directly applicable to Kansas City, KS. However, as Wyandotte County is in the lowest decile of per capita income of all 105 Kansas counties, Kansas City officials were keen to compare health measures of their residents with those of similar cities, as the current national version of the Dashboard permits, rather than to those of adjacent counties.	Responded to commonly expressed concerns regarding comparisons.
Flint, MI		
Future use	Stretching resources for the Community Health Needs Assessment (CHNA): Flint's CHNA is conducted every 3 years in a collaborative process that engages citizens, community-based organizations, health systems, and local government. Though it provides vital data for determining health improvement priorities, the CHNA is a resource-intensive undertaking for an already burdened local health department. The Dashboard offers a ready source of neighborhood-level data for a number of key indicators, lightening the burden of collection and freeing capacity to focus instead on implementation and evaluation of interventions.	Providing access to neighborhood-level measures can reduce the burden of primary data collection for CHNA and related efforts. Reducing data collection costs allows more efficient allocation of scarce public health resources (e.g., to evidence-based programs and policies, and evaluation).

stakeholder input during the development process, the site is organized from a city user's perspective: when someone clicks on a city, data appear that are preanalyzed to that city's boundaries and fully comparable across cities. Reliance on national data sets rather than primary data collection from cities facilitated comparability and scalability.

Challenges

Several important challenges remain for the City Health Dashboard and its users. First, although Dashboard data are refreshed as often as are their underlying data sets, updates to national data sets can be infrequent, and small-area estimates derived from successive versions may not always have sufficient precision to detect modest temporal trends at the city or neighborhood level. Large data sets developed for other purposes (e.g., electronic health records, claims data, food sales, social media) hold promise in this regard, although the prospect of their greater agility and national sample sizes must be balanced against the need to validate them for population health surveillance.

Second, city- and neighborhood-level estimates of health and health determinants that are derived from national data sets are just that: estimates. Communicating both their value and their attendant uncertainty (a task the 500 Cities initiative is addressing effectively[35]) is at once a challenge and an obligation in displaying such data. If disclaimers and censoring thresholds are too strong, end users are left without data or feeling overly cautious or uncertain about its interpretation. If they are too weak, however, random variation over time may be interpreted as meaningful and local initiatives shaped inappropriately.

Third, although the broad geographic reach and diverse nature of city- and community-level adoption of the Dashboard make quantitative evaluation of its impact difficult, methodical collection of use cases and associated city- and community-level health improvement initiatives will be undertaken for this purpose, complemented by Web site usage analytics. Fourth, availability of and access to national data sets against which Dashboard measures are calculated may change over time, requiring alternate sources or discontinuation of specific measures. Fifth, our focus on cities does not address the equally critical needs of rural populations; future efforts must address challenging issues of data sparsity to meet this important priority.

Finally, the proliferation of compendia of health-related measures risks leaving users with measure fatigue, as has been witnessed in health care. To foster comparability within and across such efforts, we were careful to adopt domains and measures that are rigorously derived, already in widespread use, and align with other frameworks (Table 1). Going forward, however, it will be important to balance such alignment against the value of introducing novel measures that more effectively address actionable levers of health, or are easier to collect.

Public Health Implications

The City Health Dashboard seeks to accelerate the transformation of urban population health by making widely available a new resource to spur effective city- and community-level action. Early city-level users' enthusiasm for the Dashboard reflects its unique ability to focus stakeholders clearly on both the health needs and the drivers of health in their communities, paving the way for cross-sectoral health improvement efforts. The Dashboard holds strong potential as a research resource as well—for example, in ascertaining the impact of natural experiments in municipal policies. As enthusiasm increases for local solutions to complex challenges, the City Health Dashboard promises to catalyze efforts to improve urban population health at a national scale. AJPH

CONTRIBUTORS

M. N. Gourevitch initiated the study, wrote the first draft of the article, and supervised the project. J. K. Athens designed the analytical approach and led the acquisition and analysis of data. S. E. Levine led study implementation. N. Kleiman contributed to study design and city engagement. L. E. Thorpe contributed to the analytic methods and approach. All authors participated in the interpretation of data and critical revision of the article.

ACKNOWLEDGMENTS

Funding for this initiative was provided by the Robert Wood Johnson Foundation.

We acknowledge the essential partnership of David Eichenthal and the National Resource Network in launching this effort, as well as the partnership of the National League of Cities and the International City/County Management Association in advancing its goals. We thank colleagues in the 500 Cities Project, County Health Rankings and Roadmaps, and the National Center for Health Statistics for their partnership and support. Miriam Gofine, Allegra Wilson, Shauna Ford, Sara Conderino, and Susan Kum provided essential analytic support.

CONFLICTS OF INTEREST

The authors report no conflicts of interest.

HUMAN PARTICIPANT PROTECTION

The New York University School of Medicine institutional review board determined that this study was not human participants research.

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