Ohio Opportunity Index

2012-2016 & 2014-2018

Purpose: To develop a multi-dimensional, composite, area-based measure of neighborhood socioeconomic and structural conditions to capture the social determinants of health. The Ohio Opportunity Index has the potential for wide use in research, planning and government for state, local, and community-based organizations

Step 1: Domains of opportunity are selected

The central idea of the Opportunity Index is that opportunity is a multi-dimensional construct and can be experienced in relation to a number of distinct domains. The opportunity structure in an area, which consists of social, economic, structural, and environmental factors, is measured at an area level by combining these domains. The domains for the Ohio Opportunity Index were selected using a two-stage process. Through the Infant Mortality Research Partnership, a joint research initiative between The Ohio State University and the Ohio Departments of Health, Medicaid, and Higher Education, a series of discussions with researchers, health professionals, and local and state stakeholders were held to identify domains that were key to capturing community opportunity in Ohio (Ohio GRC, 2017). These discussions were guided and informed by a review of the major conceptual frameworks in the social determinants of health literature. Central to this was the Dahlgren-Whitehead model of the determinants of health (Dahlgren et al., 2006). Another important input was early work on neighborhood opportunity mapping conducted by the Kirwan Institute at The Ohio State University (Kenitzer, et al., 2017), which was conducted to address issues of equity, particularly as they pertained to housing and sustainable urban development. Key stakeholders were asked to discuss the relative importance of different domains identified in the literature to the health and well-being of Ohioans. Domains identified as being crucial to capturing opportunity in the OOI were transportation, education, employment, housing, health, environment, and crime.

Step 2: Indicators are chosen to measure each domain

For each of the seven domains, a thorough review of the literature was completed to catalogue the most commonly used variables in the public health literature. Specifically, we assessed whether a variable was domain specific, and could theoretically capture opportunity or deprivation at a population level. Other considerations included: whether the variable could updated for future time periods, was statistically robust at a small area level, was available for the whole of Ohio from a single data source. Table 1 shows the variables included in the index by domain, a detail description, and the years used, geographic level of analysis and the source of the data.

The **transportation** domain contains 4 variables: access to public transit, average commute to work time, housholds without vehicle access and traffic proximity. These variables capture how connected areas are, and whether people living in those areas have access to public transit. Connectedness to the surrounding community can facilitate individuals' access to socio-economic opportunities, social capital, and resources (Dodson et al., 2004; Younger et al., 2008). Further, high cost transportation options (such as automobile commuting) can present a barrier to impoverished individuals, restricting where they can buy houses or find employment opportunities (Gannon & Liu, 1997).

The **education** domain contains 5 variables: educational attainment, average school performance, average free and reduced lunch participation rate, high school graduation rate, and residential internet connectivity. Education is a key componenet of the SDH due to its implications for economic status and health outcomes later in life (Krieger, 2003; Rumberger, 1987). The chosen variables approach education from multiple fronts including population level characteristics (i.e. educational attainment), school level characteristics (e.g. average school performance) and broader access to information (e.g. internet connectivity).

The **employment** domain contains 4 variables: low-wage job access (total entry-level jobs divided by total people with high-school or less education), access to workforce or job training sites, unemployment, and poverty. Access to health insurance and the financial means to maintain a healthy lifestyle are closely linked to employment. Mental and physical health has been shown to be disparate between those who are employed and unemployed and vary in regards to access to economic resources in developed countries (Brydsten et al., 2018). Research indicates that employment-targeted community interventions could provide large benefits, particularly to minority populations (Thornton et al., 2016). The inclusion of variables that measure job and job training access, attempt to capture resource availability beyond unemployment. Well implemented workforce training resources have been shown to have the ability to improve health and economic equity in disadvantaged populations (Tsui, 2010). Poor health has been recognized as being part of a negative feedback loop with poverty often called the 'health-poverty trap' (Bor et al., 2017). While it is well understood that poor health can lead to poverty through job loss and higher expenditures on health care, poverty also feeds back into poor health by stripping away an individual's resources that are necessary for better health outcomes (*Health, Income, & Poverty*, 2018). Area level measurements of self reported health have shown positive associations with economic opportunity, indicating that the linkages between health and economic status reach beyond income inequality and affect a much broader category of outcomes that the OOI attempts to capture (Venkataramani et al., 2016)

The **housing** domain contains 6 variables: median rent, median home value, concentration of existing Low-Income Housing Tax Credit (LIHTC) units, housing stock built pre-1960s, residential overcrowding and residential mobility. The variety of variables used in this domain capture multiple facets of housing characteristics that can affect an individual's access to opportunities and healthy environments through their living conditions (Gibson et al., 2011). Median rent and home value, LIHTC unit concentration, population living with overcrowding and population that moved three or more times in the last year are used to represent the economic environment of the neighborhood. Research indicates low-income neighborhoods often have poorer resource accessiblity and health outcomes (Humphrey et al., 2019). The percent of houses built pre-1960s is used as an indicator for the potential presence of lead in the houses in that area. Lead can lead to detrimental health effects (including infant mortality) that have been linked to socio-economic status (Bellinger, 2008).

The **health** domain contains 8 variables: age-adjusted mortality rate, preventable ED admits/visits, diabetes admits/diagnoses, access to grocery stores and access to medical providers. The health domain variables were selected to represent both potential and realized access to healthcare. The direct health measures capture realized access to healthcare – places where people access primary healthcare will see lower preventable ED admits, and admissions for diabetes, because the health conditions leading to these are more controlled. The measures of access were based off of the USDA Food Access Research Atlas, and used their census tract or zipcode designation for urban and rural (Economic Research Service (ERS), U.S. Department of Agriculture (USDA), 2019). Food access was restricted to grocery stores, rather than including fast food and convenience stores, due to the neighborhood disparities in healthy food options. Impoverished neighborhoods have less access to healthy food options compared to wealthy neighborhoods, restricting residents ability to make better food choices (Hilmers et al., 2012). Research also indicates that inadequate neighborhood access to medical providers, such as cancer screening facilities, can have a larger impact on an individual's health outcome than those individual's risk factors such as obesity (Kurani et al., 2020).

The **crime** domain contains 5 variables: homicide, aggravated assault and sexual assault; robbery; burglary, larceny-theft and motor vehicle theft; public drunkenness and DUI; and drug involved crimes. High levels of crime have been shown to exacerbate neighborhood level opportunity to poor health outcomes, particularly in areas that are low-income or resource scarce (Humphrey et al., 2019). Further, fear of crime has been shown to be associated with negative health outcomes (Lorenc et al., 2012).

Multiple categories of crime are considered in this construct because research indicates that crime is affected by economic opportunity in different ways. Economic inequality strongly impacts violent crime, but has little to no effect on property crime, and poverty effects property crime rates, but not violent crime (Kelly, 2000). All crime rates for this domain are calculated by dividing the counts of a specific type of crimes by population derived from the U.S. Census. Every crime variable is inverted as low neighborhood crime rate is indicative of better opportunities.

The **environment** domain contains 4 variables: access to green space, PM2.5 levels in air, walkability, and urban landcover. PM2.5 is an air pollutant which has been shown to be a major driver in health disparities in low SES neighborhoods (Morello-Frosch et al., 2011). Distance to green space, walkability and the proportion of urban land cover represent the built environment (Manson, Steven et al., 2019). Access to greenspace and urban landscapes that encourage active transport, resulting in increased walkability, have been shown shown to be linked to better mental and physical health globally (Dadvand & Nieuwenhuijsen, 2019; Sallis et al., 2020).

Step 3: Variables are standardized and combined to form domains

The OOI was developed using census tracts or zip codes as the geographic area of aggregation. The variables discussed above were first obtained at the census tract- or zip code-level. Since the aim is to obtain a single measure for each domain of opportunity, it is necessary to standardize all the variables to the same measurement scale so they can be easily combined.

To standardize the variable, we converted each into a z-score. Some z-scores are reversed by multiplying the values by negative one to make positive and negative values comparable across indicators. For example, the rate of diabetes admissions is reversed because a greater number of admissions (a high rate) is a negative outcome. The proportion of people with a college education is not reversed because a higher percentage is a positive outcome. See Table 1 for which variables were reversed.

Variable z-scores were combined using an unweighted mean within in each domain for each census tract or zip code. The domain scores were then re-standardized to have a mean of zero and a standard deviation of one.

Step 4: Domain scores are ranked and transformed into an exponential distribution.

When combining the domains to form an overall index, it is important that the scores of each domain are comparable and that the weighting of domains is not distorted by the fact that domains may have different distributions. It is also important to select a method of combination that does not result in deprivation in one domain being cancelled out by lack of deprivation on another domain. This is sometimes referred to as a "cancellation effect." To achieve this, each domain is standardized by ranking the scores from highest to least opportunity. This ensures the domains have identical distributions with the same range. The z-scores for each domain are ranked and scaled to a range between 0 and 1

- The highest opportunity → $R = 1/N$
- The least opportunity → $R = N/N$

  Where R is rank and N is the number of observations

Next, we transformed the ranked domain scores using an exponential transformation, making each domain's values range from 0 to 100 based on the method suggested by (Noble et al., 2006). The exponential transformation has the advantage that every domain is converted to an identical distribution but also emphasizes the extreme 'tails' of the distribution and so facilitates the identification of the locations with the least opportunity. The transformed domain, X, is given by:

$$X = -23\ln\left\{1 - R\left[1 - \exp - \left(\frac{100}{23}\right)\right]\right\}$$

With the exponential transformation, the census tracts or zip codes have scores ranging between 0 (least opportunity) and 100 (most opportunity) on each domain. The scores increase exponentially so that the census tracts or zip codes with the highest opportunity have more prominence.

Step 5: Domains are combined into a single area measure of opportunity

In the final step, the domain scores are added together and divided by the number of domains (7) to develop the full Opportunity Index Score, which ranges between 0 and 100.

Using this methodology, higher index values indicate higher levels of neighborhood opportunity. For example, for a rural area with poor access to schools, fewer job opportunities, and high levels of poverty, we would anticipate a low opportunity score. In contrast, a geography located in an urban setting with low crime, high housing values, and strong schools and educational attainment would be expected to have a high opportunity score.

Limitations: Many of the variables used to construct domain scores are derived from the U.S. Census American Community Survey (ACS). Small area estimates from the ACS are period estimates, meaning they are averages derived from data collected over a 5 year period, rather than using data collected at a single point in time. Guidelines produced by the Census Bureau caution against using overlapping period estimates to make comparisons over time. Thus, one significant limitation of the OOI is the inability to construct independent indices for periods that are less than 5 years apart.

Another limitation is related to geographic aggregation. The OOI was calculated for specific geographies (census tract or zip code). As described above, raw date (e.g., percents or rates) were transformed, ranked and transformed again to make both domain indices and the full opportunity index. Given the level of data manipulation used in the process, it is inappropriate to aggregate the small area estimates to larger geographic areas, such as census tracts. Rather, if the OOI is required for a different level of geography, the index creation process should be repeated using the desired geographic boundary (e.g., county) in the very first step.

Two of the health indicators (preventable ED visits and diabetes admissions) were constructed using Medicaid claims data. This is an incomplete picture of these conditions as they do not contain data from private payors. There is a valid argument that many of these preventable visits/admissions are concentrated in the low-income, Medicaid eligible population. However, the lack of private payor claims may bias small area estimates, exacerbating rates in areas with large low-income populations.

The seven domain scores were not weighted before being combined into the single measure opportunity index. Most indices of deprivation currently in used use some form of domain weights, acknowledging that not all domains contribute equally to opportunity structure (e.g., high levels of education creates more opportunity than a good physical environment). There is need for further work on the selection of appropriate weights for combining domains.

Domain	Variable	Description	Invert	Years	Scale	Source†
Trans-portation	Public Transit Access	% of the population that has access to public transportation (including taxi)		2014-2018	Census Tract or ZCTA	ACS
	Average Commute Time	Average time spent commuting to work	X	2014-2018	Census Tract or ZCTA	ACS
	Households without vehicle access	% of households in a Census Tract or ZCTA without access to a vehicle	X	2014-2018	Census Tract or ZCTA	ACS
	Traffic Proximity	Average annual daily vehicle traffic by distance	X	2016-2018	Census Tract or ZCTA	EJSCREEN
Education	Educational attainment	% of population with an Associate's degree or higher		2014-2018	Census Tract or ZCTA	ACS
	School performance	Average performance index of three closest schools		2017-2018	Address	ODE
	Students on free and reduced lunch	Average free/reduced lunch rate of three closest schools	X	2017-2018	Address	ODE
	High School graduation rate	Average high school graduation rate of three closest schools		2017-2018	Address	ODE
	Residential internet connection availability	# of residential fixed high-speed connections per 1,000 households		2017	Census Tract or ZCTA	FCC
Employ-ment	Low-wage job access	Ratio of entry-level jobs to non-college educated workforce	X	2014-2018	Census Tract or ZCTA	ACS
	Access to workforce or job training sites	# of industrial, trading or technical schools within a Census Tract or ZCTA		2016-2018	Address	INFOGROUP
	Unemployment	Unemployment rate	X	2014-2018	Census Tract or ZCTA	ACS
	Poverty	% of family living below the federal poverty line	X	2014-2018	Census Tract or ZCTA	ACS
Housing	Median Rent	Median rent in dollars		2014-2018	Census Tract or ZCTA	ACS
	Median Home Value	Median home value in dollars		2014-2018	Census Tract or ZCTA	ACS
	Concentration of existing LIHTC Units	% of family low-income housing tax credit households	X	2020	Census Tract or ZCTA	OHFA
	Housing stock built pre-1960s	% of homes built pre-1960s	X	2016-2018	Census Tract or ZCTA	EJSCREEN
	Residential overcrowding	Ratio of people living with overcrowding	X	2014-2018	Census Tract or ZCTA	ACS
	Residential mobility	% of population that has moved three+ times in the last year	X	2014-2018	Census Tract or ZCTA	ACS
Health	Geographic access to Medical Providers	# of medical providers within 1 mile (urban) or 10 miles (rural) of Census Tract or ZCTA		2016-2018	Address	INFOGROUP
	Geographic access to healthy food options	# of grocery stores within 1 mile (urban) or 10 miles (rural) of Census Tract or ZCTA		2016-2018	Address	INFOGROUP
	Age-adjusted mortality	Overall age-adjusted mortality rate	X	2016-2018	Address	ODH

	Preventable ED admits/visits	% of ED visits for a preventable medical condition, Medicaid beneficiaries	X	2016-2018	Address	ODM
	Diabetes admits/diagnoses	% of Medicaid inpatient admissions with a primary diagnosis of diabetes among	X	2016-2018	Address	ODM
Crime	Homicide, aggravated and sexual assault	Rate for aggravated assault, homicide and sexual assault per 100,000 population	X	2016-2018	Address	ODPS
	Robbery	Rate for robbery per 100,000 population	X	2016-2018	Address	ODPS
	Burglary, larceny, and motor vehicle theft	Rate for burglary, larceny-theft and motor vehicle theft per 100,000 population	X	2016-2018	Address	ODPS
	Public drunkenness and DUI	Rate for DUI and disorderly conduct per 100,000 population	X	2016-2018	Address	ODPS
	Drug involved crimes	Rate for drug related offense per 100,000 population	X	2016-2018	Address	ODPS
Environ-ment	Access to green space	Distance to nearest park	X	2018	Census Tract or ZCTA	TFPL
	PM2.5 levels	Annual average $PM_{2.5}$ levels in $\mu g/m^3$	X	2016-2018	Census Tract or ZCTA	EJSCREEN
	Walkability	Ease of walking access through the built environment		2015	Census Tract or ZCTA	EPA
	Percent high density urban landcover	Proportion of high density urban landcover per Census Tract or ZCTA		2011	Census Tract or ZCTA	IPUMS

Table 1. Domains, Variables and Data Sources Used for the Ohio Opportunity Index

†ACS= American Community Survey; EJSCREEN=EPA Environmental Justice Screening and Mapping Tool; ODE=Ohio Department of Education; INFOGROUP=INFOGROUP Business Listings; ODH=Ohio Department of Health, Vital Statistics; ODM= Ohio Department of Medicaid Claims Files; ODPS= Ohio Department of Public Safety, Office of Criminal Justice Services; TFPL=Trust for Public Land

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