**ORIGINAL RESEARCH**

# Spatial and Temporal Trends in Multidimensional Poverty in the United States over the Last Decade

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## Abstract

This paper undertakes a comprehensive analysis of multidimensional poverty in the United States over the last decade. It provides estimates of multidimensional poverty over more than a decade, from 2008 to 2019, which covers the Great Recession and the recovery following the recession when major policy changes such as the Affordable Care Act were implemented. For the first time, spatial trends in estimates of multidimensional poverty are also provided. We measure annual poverty levels in 4 regions, 50 states and examine the relation between multidimensional poverty and neighborhood characteristics. We find that on average, 13 percent of the United States population was multidimensional poor. Poverty rates were high in the South and the West and among young adults, immigrants and Hispanics. Alternative indices of multidimensional poverty show consistent trends; multidimensional poverty in the United States rose between 2008 and 2010 and then gradually declined. However, more than a quarter of individuals with incomes above the poverty threshold remained multidimensional poor. This underscores the fact that income does not always capture deprivation experienced by individuals. Policies geared towards affordable housing, health insurance and higher education will help reduce multidimensional poverty in the United States.

## 1 Introduction

Poverty has been traditionally regarded as income shortfall of an individual. However, income levels do not accurately reflect an individual's quality of life. Despite having income above a poverty threshold, an individual may still be deprived in other dimensions such as education, housing, or health. When an individual suffers multiple such deprivations at the same time, the consequences for quality of life far exceed the sum of each

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separate deprivation (Stiglitz et. al., 2009). Hence the need to measure multidimensional poverty.

In the last decade or so, a multidimensional approach to poverty measurement has become increasingly prevalent. Since 2010, the United Nations Human Development Report has annually published a multidimensional poverty index (UN-MPI) for more than 100 developing countries.[1] Multidimensional poverty rates have also been published in developed countries such as Australia, China, Germany, Japan and the United Kingdom.[2] The official poverty measure in the United States (U.S.) has been criticized for being outdated (Smeeding, 2006) and alternative measures such as the Supplemental Poverty Measure are published annually (Garner & Short, 2010). In recent years, there is a growing interest in U.S. regarding multidimensional poverty among its population.[3]

This paper contributes to the literature by providing a comprehensive picture of multidimensional poverty in the U.S. over time and across regions. The paper estimates multidimensional poverty in the U.S. over the longest period, from 2008 to 2019 and for the first time, provides estimates of multidimensional poverty in 4 regions and all 50 states in each year. Our estimates show that over the past 12 years, 13 percent of non-elderly adults in the U.S. were multidimensional poor, that is, they were deprived in at least two of the six quality of life indicators. At the peak of the recession, more than 15 percent of the population was multidimensional poor. We estimate three different indices, and all show consistent trends; multidimensional poverty in the U.S. rose between 2008 and 2010 and then gradually declined.

Between 2008 and 2019, about 13 percent were multidimensional poor and about 12.5 percent were income poor. However when we analyze how many of the multidimensional poor were also income poor, we find a very small overlap. Only 5.5 percent were both income poor and multidimensional poor. Multidimensional poverty was, in fact, more prevalent among individuals with incomes between 100 to 200 percent of the poverty threshold. A majority of multidimensional poor lacked any health insurance (public or private), had severe housing cost burden and lacked high school education. Multidimensional poverty rates were higher among children and young adults (18–24 years old), among single-headed families, and among immigrants. We find that Hispanics had the highest proportion of multidimensional poor population even when we altered weights attached to different indicators. Our analysis help us make a stronger case that poverty in the United States should be evaluated using indicators, which capture deprivation beyond income.

In terms of spatial trends, we find that multidimensional poverty was more prevalent in the South and the West; the states of California, Texas and Florida had some of the highest proportions of multidimensional poor. We also test whether there was a greater probability that multidimensional poor in the United States tended to live in neighborhoods with certain characteristics such as high crime rates and poor air and water quality.

The remainder of the paper is structured as follows. In Sect. 2 we provide a detailed overview of the recent literature on multidimensional poverty in the U.S and highlight

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[1] For most recent estimates of UN-MPI see http://hdr.undp.org/en/2020-MPI and related documentation, see https://ophi.org.uk/multidimensional-poverty-index/.

[2] For examples, see Martinez Jr. and Peralez (2017) for Australia, Yang and Mukhopadhaya (2019) for China, D'Ambrosio et al. (2014) for Japan, Nowak and Scheicher (2017), Suppa (2018) for Germany, Sevinc (2020) for the United Kingdom and Weziak-Bialowolska (2016) for the European Union.

[3] See Dhongde and Haveman (2017), Dhongde et al. (2019), Glassman (2019, 2021), Mitra and Brucker (2019), Dhongde (2020) and Dhongde and Dong (2022).

specific contributions of this paper. We also discuss the data used and explain our choice of indicators in this section. In Sect. 3, we offer a framework to understand alternative indices in the literature. We estimate each of these indicators and provide trends over time. This section also contains discussion on the overlap between multidimensional poverty and income poverty. In Sect. 4, multidimensional poverty experienced by different population groups is discussed. Section 5 tests the sensitivity of our estimates to some of the assumptions made. In Sect. 6, we provide annual statewide estimates of poverty between 2008 and 2019 and examine how neighborhood characteristics such as crime rate, air and water pollution were correlated with multidimensional poverty. Section 7 concludes with a discussion on some of the limitations of the analysis.

## 2 Background

### 2.1 Previous Literature

The literature on multidimensional poverty in the U.S. is fairly recent (see Table 1). Dhongde and Haveman (2017) were the first to estimate the extent of multidimensional deprivation in the United States since the onset of the Great Recession, from 2008 to 2013.[4] Mitra and Brucker (2019) and Glassman (2019, 2021) estimated multidimensional poverty in the post-recession period, the former estimated multidimensional poverty between 2013 and 2017 and the latter provided estimates for 2016–2017; Glassman (2021) revised and extended those estimates for 2018–2019.[5] Recently, Dhongde (2020) estimated multidimensional economic deprivation in the U.S. early on during the Covid-19 pandemic using data from April 2020. This paper contributes to this recent literature by providing estimates of multidimensional poverty in the U.S. over the longest time (12 years), from 2008 to 2019, covering the period of the Great Recession as well as economic recovery.

Previous studies have largely estimated multidimensional poverty in the U.S. using the Alkire and Foster (AF, 2011) indices. There have been several alternative indices, which have been proposed since the AF indices.[6] In particular, Dhongde et al. (2019) proposed a new index with additional properties and measured multidimensional deprivation in the U.S. In Sect. 3, we show that the framework of Dhongde et al. (2019) index is broader and that the AF indices are, in fact, special cases of this more general index. We estimate three alternative indices, the headcount ratio, the adjusted headcount ratio from AF (2011) and the Dhongde et al. (2019) index, and find that trends in multidimensional poverty were consistent. Multidimensional poverty in the U.S. increased during the Great Recession (2008–2010) and then declined during the recovery period.

There are two large surveys that have been used to measure multidimensional poverty in the U.S., namely, the American Community Survey (ACS) and the Current Population Survey (CPS). Both are annual surveys conducted by the Census Bureau (see Fox et al., 2020 for a comparison of the CPS and the ACS). Most of the prior literature has used the

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[4] Previous studies used U.S. data to demonstrate applications of multidimensional poverty but were limited to estimates from a single year (e.g., Alkire and Foster, 2011; Mitra and Brucker, 2016).

[5] Glassman (2019, 2021) provide values of multidimensional poverty estimates in 2016–2017 and 2018–2019 respectively though Fig. 2 in both the working papers shows a trend line since 2009–2010.

[6] See Dhongde and Dong (2022) for application of alternative indices to measure multidimensional poverty in the United States.

**Table 1** Overview of literature on multidimensional poverty in the U.S

| | Estimates from-to | No. Years | Data | Indicator threshold | Index | Income class | State-wide | Poverty overlap | Environ charc |
|---|---|---|---|---|---|---|---|---|---|
| Dhongde and Haveman (2017) | 2008–2013 | 6 | ACS | 2/6 | AF | Y | Y | Y | N |
| Dhongde et al. (2019) | 2008–2015 | 8 | ACS | 4/9 | New | N | N | N | N |
| Glassman (2019)* | 2016–2017 | 2 | ACS, CPS | 2/6 | AF | N | Y | Y | Y |
| Mitra and Brucker (2019) | 2013–2017 | 5 | CPS | 2/5 | AF | N | N | N | N |
| Dhongde (2020) | April, 2020 | 1< | SHED | 2/4 | AF | Y | N | N | N |
| Glassman (2021)* | 2018–2019 | 2 | ACS, ADI | 2/6 | AF | N | Y | Y | N |
| Dhongde and Dong (2022) | 2009–2018 | 10 | CPS | 2/5 | Multiple | N | N | N | N |
| **This paper** | **2008–2019** | **12** | **ACS** | **2/6** | **AF** + Dhongde et al. (2019) | **Y** | **Y** | **Y** | **Y** |

*Indicates a report/working paper

*AF* Alkire and Foster (2011), *ACS* American Community Survey, *CPS* Current Population Survey, *SHED* Survey of Household Economics and Decision-making, *ADI* Area Deprivation Index

Indicator threshold shows the threshold for multidimensional poverty; e.g. 2/6 implies individuals deprived in 2 out of 6 indicators are identified as multidimensional poor

We have included a majority of studies in the U.S. in this review and omission of any study is purely accidental

ACS for measuring multidimensional poverty largely because compared to CPS, the ACS compiles detailed information on indicators besides income such as housing costs, time spent at work and on commute and so on. However, the one drawback of the ACS is a lack of data on health. The only health-related data available in the ACS is on individuals' disabilities. The CPS asks individuals to self-assess their health ranking. As we discuss in the next section, the choice of indicators to measure multidimensional poverty is limited by the availability of data in the ACS.

It is important to understand the relation between multidimensional poverty and income poverty. Dhongde and Haveman (2017), Glassman (2019, 2021) have studied such an overlap in the U.S. context. We innovate by estimating a redundancy measure between income poverty in the U.S. and deprivation in each indictor and find no strong relation between these two. In Sect. 3, we also estimate the prevalence of multidimensional poverty among other income classes (not just among the income poor). Except for Dhongde and Haveman (2017), none of the previous studies have estimated multidimensional poverty rates by income classes. We find that multidimensional poverty was prevalent among individuals having incomes just above the poverty threshold.

The paper also uses a finer classification of some of the demographic categories (Sect. 4). For instance, instead of the typical three categories for age (children below 18, adults between 18 and 64, and the elderly who are 65 and above) used in most studies (e.g. Dhongde et. al., (2019) Glassman, (2019, 2021), Mitra and Brucker, (2019)), we consider seven different age categories and are able to highlight differences in poverty rates among, say, young adults (18 to 24 years) and older adults (55 to 64). Similarly, we estimate poverty rates for different family types (married, female or male-headed households) since single headed households are often at a greater risk of being poor. None of the previous studies, except for Dhongde and Haveman (2017), have measured multidimensional poverty by family types.

Previous literature measuring multidimensional poverty in the U.S. has typically undertaken some kind of sensitivity analysis. For example, sensitivity of the benchmark index is tested by varying the number of indicators used as cut-off to identify the poor (Mitra & Brucker, 2019, Dhongde, 2020, Glassman 2021), threshold of any indicator (Dhongde & Haveman, 2017; Mitra & Brucker, 2019) and indicator weights (Dhongde et al., 2019). We add to the previous sensitivity tests, by alternately excluding and mandating deprivation in certain indicators to be counted towards multidimensional poverty. In Sect. 5, we also analyze whether certain indicators unduly influence poverty estimates among individuals belonging to a particular race or ethnicity.

In addition to temporal trends, we also analyze spatial patterns in multidimensional poverty (Sect. 6). We estimate poverty indices in 4 regions and all 50 states each year. This is an important contribution of the paper since none of the previous papers provide regional estimates and a few provide statewide estimates for at the most two years.[7] In this paper, for the first time, we estimate multidimensional poverty rates at state level for 12 years. Furthermore, we test whether multidimensional poor tend to live in particular type of neighborhoods. Previous studies in the U.S. have not been able to include environmental characteristics such as pollution while measuring multidimensional poverty largely because Census surveys such as the ACS and the CPS do not collect this information for

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[7] Glassman (2019) does not provide statewide estimates but provides changes in state official poverty rates and multidimensional poverty rates between 2016 and 2017. Glassman (2021) provides statewide poverty rates for 2019.

individuals. Glassman (2019) compiled county level data (separately of ACS or the CPS) on three indicators, namely crime rates, air quality and food environment index.[8] An individual was deprived if she lived in a county in the top 10th percentile of any two of the above three indicators. However, county sizes in the U.S. vary significantly. For example, the San Bernandino County in California is more than 20,000 square miles in area whereas the Lincoln County in Wyoming is less than 5000 square miles. Depending on where an individual resides within a county, she/he may not be impacted and the average values of pollution will not capture this impact. Hence, we do not use county level data as an indicator of an individual's multidimensional poverty. Our index relies solely on an individual's personal and household characteristics. Instead, we identify individuals' location using the lowest level of geographical information available in the ACS. Using data on neighborhood characteristics such as crime rates, pollution levels, we estimate regression models to examine the correlation between multidimensional poverty and the environment in which an individual resides. This kind of analysis has not been undertaken in the previous literature.

## 2.2 Data

We use annual data from the ACS, primarily because the ACS is the largest household survey in the U.S. The ACS has much larger coverage with more than 3 million individuals compared with the CPS annual sample size of about 100,000. We compile data between 2008 and 2019; data from previous rounds (2005–2007) is not strictly comparable due to changes made to the survey and 2019 is the latest year for which data was publicly available. We use the annual Public Use Microdata Sample (PUMS) files, which provide data from areas with population of 65,000 or more. PUMS is a sample of population and housing unit records from the ACS; the 1-year ACS PUMS file represents about 1 percent of the total United States population. ACS 1-year estimates describe the population and characteristics of an area for the full year, not for any specific day or period within the year. Individual records are replicated using person weights. Data on individual records are matched with the same individual's household characteristics. We remove any individuals living in group quarters and focus on the non-elderly adult population (between ages 18 and 64 years) though we also provide estimates of multidimensional poverty among all age groups including children (18 and below) and the elderly (65 and above) in Sect. 4.[9]

## 2.3 Indicators of Multidimensional Poverty

The philosophical underpinnings of a multidimensional poverty index can be traced to Sen's capability approach (Sen, 1985, 1987, 1992). Sen (1987) defines "functionings" as the "doings" and "beings" that people value. It is common not to find data on actual functionings but on some of the proxies of these functionings. For example, income is not a functioning but it is may be a proxy for other functionings such as being well-nourished,

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[8] Glassman (2021) used the Area Deprivation Index (ADI) as an indicator of multidimensional poverty. The ADI is based on economic indicators at a block level such as percent of poor, unemployment rate, and so on and does not include any neighborhood indicators we consider in Sect. 6.

[9] About 5 percent of the sample in the ACS lives in group quarters (GQs). GQs include such places as college residence halls, residential treatment centers, skilled nursing facilities, group homes, military barracks, correctional facilities, and workers' dormitories. Survey values for GQs are often imputed.

or, being able to live comfortably. The United Nations Human Development Index (HDI) was an early attempt at using the capabilities approach to measure well-being across countries. The HDI consisted of indicators on three dimensions: health, education and standard of living. The HDI compiles data on each of the dimensions separately and hence can be estimated using data compiled from different sources. This is often referred to as a column-first approach (Pattanaik & Xu, 2018). On the other hand, unlike the HDI, the multidimensional poverty index is based on a row-first approach and hence is a more data intensive process. In order to measure multidimensional poverty, we need data on each indicator for each individual and hence we cannot compile data from different data sources. Thus, the choice of indicators in a multidimensional index is dictated by the availability of data and how the indicators map into the functionings space (see Suppa, 2018 for a discussion).

Alkire et al. (2015) noted that any particular set of indicators is unlikely to represent deprivation in its entirety; the choice of indicators serves the practical purpose of informing efforts that seek to reduce multidimensional deprivation. Our choice of indicators relies on the information compiled in the ACS. Within the ACS, we choose indicators that are consistent with (i) the recommendations made by the Commission on the Measurement of Economic Performance and Social Progress, (Stiglitz, et al., 2009, 2018) and (ii) indicators used previously in the literature measuring multidimensional poverty in the U.S. Many studies in the U.S. cite the Stiglitz-Sen-Fitoussi Commission's report to justify their choice of dimensions.[10] The report was critical of current measures of economic performance, in particular, their inadequacy in measuring well-being in the midst of the Great Recession, and recommended eight key dimensions that should be taken into account by developed countries. Table 2 lists six of these dimensions and corresponding indicators on which data is available in the ACS. ACS data was not available on two of the dimensions recommended by the commission, namely, a lack of political voice and governance, and personal activities.[11] Compared to the United States Census (ACS and the CPS), the EU-SILC (EU Statistics on Income and Living Conditions) data collects information on more indicators of well-being such as health status (chronic illness), housing quality (leaky roof, damp walls), material deprivation (affordable meals and consumer durables), and environmental factors (noise and air pollution).[12]

As seen from Table 2, most of these indicators are commonly used in measuring multidimensional poverty in the U.S. As noted previously, the only health data available in the ACS is on an individual's disabilities. We identify an individual as deprived in the health dimension if he/she has two or more disabilities. A commonly used indicator of education in the literature is whether an individual received at least a high-school diploma and that of economic security is whether an individual had any type (public or private) health insurance. In order to measure housing quality, we do not have data in the ACS on household assets or material possessions. ACS compiles data on housing facilities such as plumbing

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[10] See Dhongde and Haveman (2017), Mitra and Brucker, (2019), Dhongde et al. (2019). For other reports on well-being, see the Federal Reserve Bank's Report on the Economic Well-Being of U.S. Households (2016), the Gallup-Healthways Report in the U.S. and the OECD report by Stiglitz et al., (2018) which built upon the previous work of the Stiglitz-Sen-Fitoussi Commission.

[11] Mitra and Brucker (2019) and Dhongde and Dong (2022) use data on unemployment in the CPS as an indicator for personal activities. Unlike in the CPS, in the ACS, unemployed individuals are identified as those who were actively looking for work in the last 4 weeks. Hence, in the ACS unemployment can be a result in the short term and may not always indicate deprivation. Suppa (2021) proposes a multidimensional index to measure deprivation in social participation.

[12] See Nolan and Whelan (2010) and Alkire and Apablaza (2017) for applications with EU-SILC data.

**Table 2** Indicators used to measure multidimensional poverty in the United States

| Dimensions Stiglitz et al. (2009) | Indicators | Thresholds | Previous Studies using the indicator | % below threshold |
|---|---|---|---|---|
| Health | Disabilities | Two or more out of six disabilities: hearing, vision, cognition, ambulation, serious difficulty with self-care (e.g., bathing and dressing), or performing independent tasks (e.g., shopping) | Dhongde and Haveman (2017) Glassman (2019); Dhongde et. al. (2019) | 4.6% |
| Education | High school education | Not having received at least a high school diploma | Dhongde and Haveman (2017) Glassman (2019, 2021) Mitra and Brucker (2016, 2019) Dhongde et. al. (2019) Dhongde and Dong (2022) | 10.2% |
| Economic Security | Health insurance | Lack of any type of health insurance; public or private | Dhongde and Haveman (2017) Glassman (2019, 2021) Mitra and Brucker (2016, 2019) Dhongde et. al. (2019) Dhongde and Dong (2022) | 16.9% |
| Std. of Living | Housing costs as a percentage of household income | Severe housing burden: monthly owner costs or gross rent in excess of 50% of household income | Dhongde and Haveman (2017) Glassman (2019) Dhongde et. al. (2019) | 12.1% |
| Social Connections | English fluency | Lives in a household where no person, 14 and over, speaks English only or speaks a language other than English at home and speaks English very well | Dhongde and Haveman (2017) Glassman (2019) Dhongde et. al. (2019) | 4.6% |
| Housing Quality | Number of persons per room in a housing unit | Overcrowding: unit has more than one occupant per room | Dhongde and Haveman (2017) Glassman (2019, 2021) Dhongde et. al. (2019) | 6.2% |

Average percentage is calculated using 12 years' values and for non-elderly adults (18–64) below the threshold

Data on disability, education, and health insurance are available at the individual level. Data on housing costs, English fluency, and rooms per person is compiled at the household level and assigned to individuals within the household
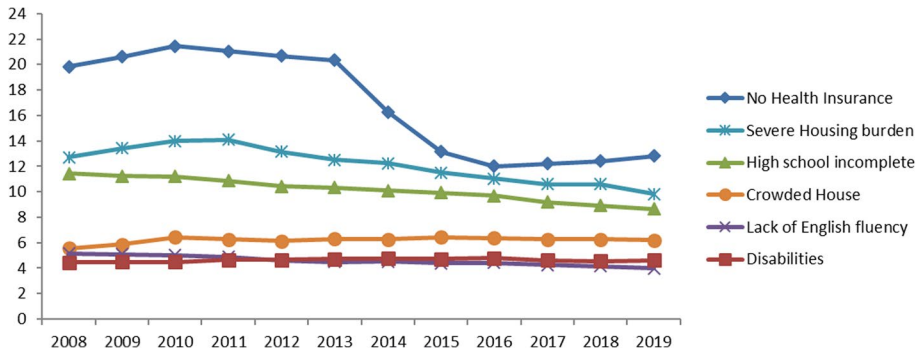
**Fig. 1** Trends in deprivation in multiple indicators of deprivation. All values are given as percent of the non-elderly adult population (18 to 64 years)

(e.g., hot/cold running water, a flush toilet, a bathtub or shower) and kitchen facilities (e.g., a sink with a faucet, a stove, range, or a refrigerator). We estimated less than 1 percent of the sample lived in households without kitchen or plumbing facilities and hence did not include these indicators in our multidimensional index. Instead, we use data to identify whether an individual lived in an overcrowded house. In the ACS, we also do not have data on individuals' civic engagement, their membership in organizations, and their relationship with neighbors, and so on. Previous studies using ACS have instead used a proxy indicator of social connections and we use the same indicator. An individual is deprived in this dimension if he/she lives in households where no person, 14 and over, speaks English only or speaks a language other than English at home and speaks English very well. Finally, we consider housing costs as a proportion of the household's income to indicate an individual's standard of living.[13] Housing burden is correlated with income (see Table A1 in the Appendix) and has been used previously in lieu of income to indicate standard of living. We do not use poverty status as an indicator because we wish to identify multidimensional poor as distinct from the income poor and then measure the overlap between these two groups. Table A1 in the Appendix also shows that there is not a strong correlation in deprivation in other indicators and none of the indicators have a high redundancy measure.[14]

In Fig. 1, we plot the percentage of deprived population in each of the six indicators listed in Table 2. The trends show that the incidence of deprivation in most indicators decreased over time. The biggest decline since 2014 occured in the proportion of adults without health insurance. Between 2008 and 2013, more than 20 percent of individuals did not have any kind of health insurance. A majority of the provisions of the Affordable Care Act (ACA) were enforced in 2014. Since then, the proportion of individuals without insurance decreased, from 20 percent in 2013 to 16 percent in 2014, and 12 percent in 2016. In recent years, the proportion of individuals without any health insurance

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[13] Housing burden categories are: (i) No housing burden when less than 30 percent of household income is spent on housing costs, (ii) Moderate burden when 30 to 49.9 percent of income is spent on housing costs, and, (iii) severe burden when housing costs are 50 percent or above (Schwartz and Wilson, 2007).

[14] The Redundancy Measure shows the percentage of individuals deprived in any two indicators as a proportion of the minimum of the two marginal deprivations (in percentage) in each indicator. A high value of the measure indicates that one of the two indicators may be empirically redundant in the analysis. See Klasen and Villalobos (2020) for an application of the redundancy measure.

increased slightly. This can be partly explained by the fact that in recent years the ACA has been dismantled and applied piecewise in some states, for example, 13 states did not expand Medicaid in 2020.

The proportion of individuals with severe housing burden also declined over time, from 14 percent in 2011 to 10 percent in 2019. Compared with health insurance, housing costs, and education, a relatively lower proportion of the population was deprived in the remaining three indicators, namely, crowded housing, lack of English fluency, and disabilities. One would not expect deprivation in these indicators to vary significantly over time, as confirmed in Fig. 1. On average, about 6 percent of the population lived in a crowded house, about 5 percent had two or more disabilities, and 5 percent lived in households where no member 14 and over, spoke English fluently.

## 3 Measuring Multidimensional Poverty

### 3.1 Multidimensional Indices

A dashboard of deprivations illustrated in Fig. 1 gives the percentage of population deprived in each indicator. However, when measuring multidimensional poverty, we are interested in finding out whether individuals experience multiple deprivations *simultaneously*. Several multidimensional poverty indices have been proposed in the literature (see Pattanaik & Xu, 2018, for a review) and the choice of an index often depends on the type of data available. The indicators discussed in the previous section are measured using different types of data. For example, having health insurance or not, are binary data; education data are ordinal with multiple levels, such as less than high school, high school graduate, college graduate; housing costs are expressed as a percentage of income; and so on. In order to aggregate different type of data in one index, we convert data on all indicators to a binary (0–1) form and estimate multidimensional poverty indices based on binary data.

Let $F = \{f_1, \ldots, f_m\}, m \geq 2$, be a set of indicators and let denote $M = \{1, \ldots m\}$. The society is denoted by a set of individuals $N = \{1, 2, \ldots n\}$. Let $b_{ij}$ denote the deprivation status of individual $i$ in indicator $j$. If an individual's achievement in the $j$th indicator is below some threshold specified for the $j$th indicator, then she is deprived in that indicator and $b_{ij} = 1$. If, on the other hand, her achievement is at or above the threshold, she is not deprived in the $j$th indicator and $b_{ij} = 0$. For instance, if the threshold for education is high-school, then an individual who is a high-school dropout, is considered deprived of education and given a score of 1, if she is a college graduate, she is given a score of 0. Let $w_j, (w_j > 0)$ denote the weight assigned to indictor $j$, such that, $\left(\sum_{j=1}^{m} w_j = 1\right)$. In the benchmark case, we assign equal weights to all six indicators, $w_j = 1/6$ (in Sect. 5 we change weights on indicators). An individual $i$'s overall deprivation is given by $\left(\sum_{j=1}^{m} w_j b_{ij}\right)$. An individual is considered multidimensional poor, if and only if her overall deprivation exceeds some threshold value $\left(\sum_{j=1}^{m} w_j b_{ij}\right) \geq t$. For instance, in the benchmark case, we set the threshold equal to $t = 2/6$ so that individuals with two or more deprivations are considered multidimensional poor (for other thresholds, see Sect. 5). Using this threshold, suppose we identify $Q = \{1, 2 \ldots q\}, Q \subseteq N$, as a set of multidimensional poor. Then a general form of multidimensional poverty indices is given in Eq. (1).

$$D_\beta = \frac{1}{n} \sum_{i \in Q} \left( \sum_{j=1}^{m} w_j b_{ij} \right)^\beta \tag{1}$$

for some $\beta \geq 0$, for all $i \in N$. When $\beta = 0$, the index in Eq. (1) simply measures the proportion of multidimensional poor in the society. We call this as the multidimensional poverty index MPI, given in Eq. (2) below

$$D_0 = MPI = (q/n) \tag{2}$$

The MPI is similar to the headcount index of income poverty.[15] A limitation of the MPI is that its value does not change if a multidimensional poor becomes deprived in an additional indicator. If a multidimensional poor experiences an additional deprivation, then everything else remaining constant, we would like the deprivation index to increase. When $\beta = 1$, the index in Eq. (1), $D_1$, is a linear function of individual's deprivation scores. This is the adjusted headcount ratio proposed by Alkire and Foster (2011). Unlike $D_0$ (MPI) if a poor person becomes deprived in an additional indicator $D_1$ will increase.

When we restrict the value of $\beta$ such that $> 1$, then as an individual's deprivation score increases, the function $(\sum_{j=1}^{m} w_j b_{ij})^\beta$ increases at an increasing rate. This family of indices are based on the axiomatic framework proposed in Dhongde et al. (2019). We estimate the index by substituting $\beta = 2$, in Eq. (1). In addition to the standard axioms, the index $D_2$ satisfies an appealing property called Clustered Dimensional Deteriorations and Deprivation (CDDD). The intuition behind CDDD is that the total harm caused by two different dimensional deprivations occurring simultaneously is greater than the sum of the separate harms caused by those two dimensional deprivations occurring one at a time. The MPI $(D_0)$ and the adjusted headcount ratio $(D_1)$ do not satisfy CDDD property. The index $D_2$ is sensitive to the changes in inequality in deprivation scores.

In Table 3, we provide estimates of $D_\beta$, when $\beta = 0, 1 \, and \, 2$. The MPI $(D_0)$ calculates the proportion of multidimensional poor in the society. The adjusted headcount ratio $(D_1)$ is equal to the sum of the weighted deprivations that the multidimensional poor experience, divided by the total population and the index $D_2$ is equal to the squared sum of the weighted deprivations that the multidimensional poor experience; thus it attaches greater weight to higher deprivation scores. All three indices show a similar trend. Deprivation rose between 2008 and 2010 and then gradually declined. The average annual percentage change in these indices was between 3 to 4 percent. We also calculate standard errors for each of the deprivation indices in Table 3. Estimate of variance of the index given in (1) can be written as follows:

$$\sigma^2_{D_\beta} = \frac{1}{n-1} \sum_{i \in Q} \left[ \left( \sum_{j=1}^{m} w_j b_{ij} \right)^\beta - D_\beta \right]^2 \tag{3}$$

In the rest of our analysis, we use $(D_0)$, that is the MPI (expressed in terms of percentage) instead of either $D_1$ or $D_2$, largely because (i) the MPI is easy to interpret, (ii) it has been routinely used by previous studies and, (iii) it can be compared with the official and supplemental income poverty headcount.

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[15] The MPI is also referred to as the multidimensional deprivation index (MDI) by Dhongde and Haveman (2017), Glassman (2019, 2021) or simply as the headcount ratio by Mitra and Brucker (2016, 2019).

**Table 3** Multidimensional poverty: Alternative indices

| | Av % Ch | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $D_0$ | −3.23 | 0.146 | 0.149 | 0.155 | 0.153 | 0.146 | 0.142 | 0.127 | 0.115 | 0.109 | 0.105 | 0.103 | 0.100 |
| | | (0.000026) | (0.000026) | (0.000026) | (0.000026) | (0.000026) | (0.000025) | (0.000024) | (0.000023) | (0.000022) | (0.000022) | (0.000022) | (0.000022) |
| $D_1$ | −3.61 | 0.058 | 0.060 | 0.062 | 0.061 | 0.058 | 0.056 | 0.050 | 0.045 | 0.042 | 0.040 | 0.040 | 0.039 |
| | | (0.000161) | (0.000161) | (0.000160) | (0.000169) | (0.000158) | (0.000157) | (0.000149) | (0.000141) | (0.000137) | (0.000134) | (0.000133) | (0.000137) |
| $D_2$ | -4.09 | 0.025 | 0.026 | 0.027 | 0.026 | 0.024 | 0.024 | 0.021 | 0.019 | 0.018 | 0.017 | 0.016 | 0.016 |
| | | (0.000079) | (0.000079) | (0.000079) | (0.000082) | (0.000076) | (0.000075) | (0.000071) | (0.000067) | (0.000064) | (0.000062) | (0.000060) | (0.000062) |

Average annual percentage change in an index. Standard errors given in brackets below each value. Each value is statistically significantly different from the value in the previous year at 5% level of significance

**Table 4** Trends in multidimensional poverty and income poverty

| | Av | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| MPI | 12.9 | 14.6 | 14.9 | 15.5 | 15.3 | 14.6 | 14.2 | 12.7 | 11.5 | 10.9 | 10.5 | 10.3 | 10.0 |
| OPM | 12.3 | 11.7 | 12.9 | 13.7 | 13.7 | 13.7 | 13.6 | 13.5 | 12.4 | 11.6 | 11.2 | 10.7 | 9.4 |
| SPM | 14.0 | 14.4 | 14.4 | 15.2 | 15.5 | 15.5 | 15.4 | 15.0 | 13.8 | 13.3 | 12.4 | 12.2 | 11.2 |
| MPI and OPM | 5.3 | 5.4 | 5.9 | 6.4 | 6.6 | 6.4 | 6.2 | 5.7 | 4.9 | 4.5 | 4.2 | 4.0 | 3.7 |

All values are given as percent of the non-elderly adult population (18 to 64 years) deprived in at least two indicators. The MPI values in Table 4 are referred to as benchmark MPI in the paper
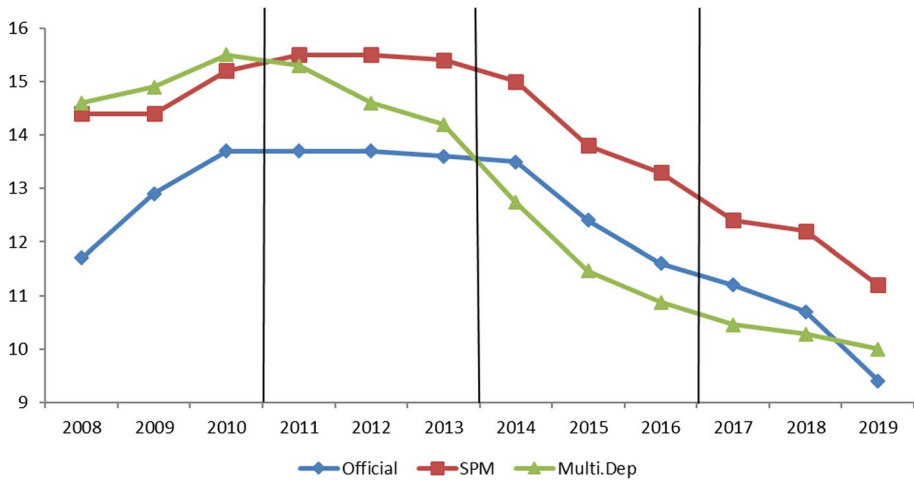


**Fig. 2** Trends in poverty and the multidimensional poverty index. All values are given as percentage of the non-elderly adult population (18 to 64 years)

## 3.2 Multidimensional Poverty and Income Poverty

In Table 4, we summarize estimates of the MPI, alongside official estimates of the official poverty measure (OPM) and the Supplemental Poverty Measure (SPM).[16] We find that on average about 13 percent of the non-elderly adult population was multidimensional poor. The average MPI was comparable with average income poverty, (average OPM was 12.6 percent and average SPM was 14.3 percent). Although the multidimensional poor and income poor were comparable in size, there was not much overlap between the two groups. Only 5.5 percent of the population on average, was income poor as well as multidimensional poor. The overlap between income poor and multidimensional poor peaked at 6.6 percent in 2011 and gradually declined to 3.7 percent in 2019. Thus, the limited overlap between income poor and multidimensional poor confirms our intuition that income often fails to capture deprivation in other dimensions affecting the quality of life. The limited

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[16] Note that the official estimates of OPM and SPM are based on CPS data so are not directly comparable with the MPI which is based on ACS data. Fox et al. (2020) provide estimates of OPM and SPM based on ACS data from 2014 to 2017.

**Table 5** Trends in multidimensional poverty by income class

| Income | Av | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| < 50% | 37.9 | 44.3 | 44.6 | 43.8 | 42.8 | 41.6 | 40.7 | 37.2 | 33.9 | 32.4 | 31.6 | 31.1 | 31.2 |
| 50–99% | 42.1 | 48.5 | 47.8 | 48.1 | 48.0 | 46.1 | 44.2 | 41.4 | 37.9 | 36.7 | 36.1 | 35.7 | 34.8 |
| 100–199% | 25.7 | 31.1 | 30.7 | 30.6 | 29.6 | 27.9 | 26.9 | 24.2 | 22.3 | 21.8 | 21.1 | 21.1 | 21.2 |
| 200–499% | 7.4 | 9.2 | 8.7 | 8.6 | 8.0 | 7.6 | 7.5 | 6.6 | 6.4 | 6.4 | 6.4 | 6.5 | 6.9 |
| 499% < | 1.2 | 1.6 | 1.4 | 1.4 | 1.2 | 1.2 | 1.3 | 1.1 | 1.1 | 1.1[+] | 1.1 | 1.2 | 1.2 |
| Benchmark | 12.9 | 14.6 | 14.9 | 15.5 | 15.3 | 14.6 | 14.2 | 12.7 | 11.5 | 10.9 | 10.5 | 10.3 | 10.0 |

All values are given as percentage of the non-elderly adult population (18 to 64 years) Standard errors are given in Appendix Table A2. All values are statistically significantly different from previous year's value at 5% except for those shown with +

overlap between income poor and multidimensional poor has also been observed in other developed countries. For example, Suppa (2018) estimated about 5% of German population, and Alkire and Fang (2019) found about 2% of population in China was both income poor and multidimensional poor.

Figure 2 plots trends in the MPI alongside those in the two poverty measures, namely OPM and SPM. Suppose we divide the time period in four quarters: (i) Recession: 2008 to 2010, (ii) Short-term recovery: 2011 to 2013, and (iii) Long-term recovery: 2014 to 2016 and (iv) Recent years: 2017 to 2019. During the recession, all three indices peaked; the MPI and OPM peaked in 2010, whereas the SPM peaked in 2011. The short-term recovery period covers years immediately following the recession. The MPI started a downward trend almost immediately in 2011. However, the OPM and SPM remained more or less constant. This suggests that compared to incomes, recovery was faster in other indicators. During this period, the estimated proportion of multidimensional poor was between the two income poverty estimates. In the long-term recovery period (2015 to 2019) we find that all three measures poverty indices decreased, but the MPI had the most rapid decline. However, in more recent years (2017 to 2019), the MPI declined at a slower rate than income poverty. With the onset of the Covid-19 pandemic and the resulting economic shock, it will be interesting to see how these trends emerge post 2019.

### 3.3 Multidimensional Poverty by Income Class

In Table 5, we list the MPI for five different income-poverty categories. We find that the decline in MPI over the years was robust across all income groups. Expectedly multidimensional poverty levels were high among income poor. On average, over time, about 38.5 percent individuals in extreme poverty (incomes less than 50 percent of the poverty threshold) were multidimensional poor. The highest incidence of multidimensional poor was, however among individuals with incomes just below poverty (incomes between 50 and 100 percent of the poverty threshold). Nearly 43 percent of individuals in this income category were multidimensional poor. If we consider the entire 12-year span, in every year, a greater proportion of individuals closer to the poverty threshold were multidimensional poor, compared to individuals further below the poverty threshold.

Importantly, more than a quarter of individuals with income just above the poverty threshold (100 to 200 percent of the poverty line) were multidimensional poor. Despite having incomes above poverty thresholds, these individuals were deprived in two or more

indicators. Recall that the correlation between income poor and deprivation in each of the six indicators (except for housing burden) was not strong. This underscores our argument that income poverty often fails to capture deprivation in other dimensions affecting the quality of life. Finally, only 1.2 percent of individuals with incomes more than 500 percent of the poverty threshold were identified as multidimensional poor. This is reassuring since it tells us that our estimates of the MPI capture very few individuals who had high incomes and "chose" in some ways, to remain deprived in two or more of the indicators. For example, in Sect. 5 we consider only those individuals as deprived in the housing dimension if their household income was less than $75,000 and they experienced severe housing burden. With the additional income qualification, we find that our MPI estimates do not change significantly.

# 4 Multidimensional Poverty by Demographic Groups

Of particular interest for policy purposes is how deprivation varies by age, gender, race/ ethnicity, nativity, and household type. In Table 6, we show MPI estimates across multiple demographic groups over the 12 years. The table also shows the average values of the MPI, and the average annual change in the MPI.

## 4.1 Multidimensional Poverty by Age Groups

We find that among all age groups the average MPI was highest (15.6 percent) among children.[17] High multidimensional poverty levels were consistent with income poverty rates among children in the U.S. which are typically high. Multidimensional poverty rates were also high among the young adults (18–24 years old) especially during the recession. In 2010, nearly one in every five young adults was multidimensional poor.

So far, in our analysis, we estimated multidimensional poverty among the non-elderly (18–64 years) largely because the indicators chosen are more relevant for this age group. The extent of deprivation experienced by the elderly (65 years and above) differs significantly from the rest of the adult population. For example, compared to almost 17 percent of non-elderly adults lacking health insurance, just about one percent elderly had no health insurance, largely due to provisions of Medicare. Similarly, only about 2 percent of the elderly lived in a crowded house compared with 6 percent of non-elderly adults. On the other hand, nearly 20 percent of the elderly had two or more disabilities compared with 4.6 percent of non-elderly with multiple disabilities. We estimate that on average, 12.3 percent of elderly were multidimensional poor over the decade. When we consider the entire population, comprising of children, non-elderly and elderly adults, we find that on average 13.5 percent were multidimensional poor.

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[17] Following the literature, we assigned children years of schooling of the head of the household. Disability data were missing for a majority of children; so we assigned the highest disability score among adults in the same household. For all other indicators, children and adults belonging to the same household were assigned the same values.

**Table 6** Trends in multidimensional poverty index by demographic groups

| | Av | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | Chg |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Age groups** | | | | | | | | | | | | | | |
| 17-below | 15.6 | 17.5 | 17.7 | 17.7+ | 17.1 | 16.4 | 16.1 | 15.6 | 14.8 | 14.4 | 13.8 | 13.5 | 13.2 | −2.5 |
| 18 to 24 | 14.7 | 18.2 | 18.8 | 19.9 | 18.3 | 16.8 | 16.2 | 14.0 | 11.9 | 11.0 | 10.7 | 10.4 | 10.2 | −4.9 |
| 25 to 34 | 14.1 | 17.4 | 17.3 | 17.9 | 17.1 | 16.2 | 15.5 | 13.8 | 12.2 | 11.2 | 10.5 | 10.1 | 9.8 | −5.0 |
| 35 to 44 | 13.9 | 14.7 | 15.4 | 16.0 | 16.1 | 15.4 | 15.3 | 14.0 | 12.9 | 12.3 | 11.8 | 11.5 | 11.4 | −2.2 |
| 45 to 54 | 11.7 | 12.1 | 12.6 | 13.3 | 13.6 | 13.1 | 13.0 | 11.8 | 10.6 | 10.3 | 10.1 | 10.2 | 9.8 | −1.8 |
| 55 to 64 | 10.7 | 11.3 | 11.5 | 11.9 | 12.2 | 11.9 | 11.5 | 10.6 | 9.7 | 9.5 | 9.2 | 9.3 | 9.1 | −1.9 |
| 65-above | 12.3 | 14.9 | 14.2 | 13.7 | 13.7 | 12.7 | 12.3 | 12.1 | 11.6 | 11.3 | 10.8 | 10.5 | 10.2 | −3.4 |
| Entire Pop | 13.5 | 15.4 | 15.5 | 15.8 | 15.5 | 14.8 | 14.4 | 13.3 | 12.3 | 11.8 | 11.3 | 10.9 | 10.6 | −3.3 |
| **Gender** | | | | | | | | | | | | | | |
| Female | 12.4 | 13.8 | 14.1 | 14.8 | 14.6 | 14.0 | 13.7 | 13.2 | 10.9 | 10.4 | 10.0 | 9.9 | 9.7 | −3.4 |
| Male | 13.4 | 15.4 | 15.8 | 16.3 | 16.0 | 15.2 | 14.7 | 12.3 | 12.0 | 11.3 | 10.9 | 10.7 | 10.4 | −3.1 |
| **Family type** | | | | | | | | | | | | | | |
| Married | 10.1 | 11.2 | 11.5 | 12.1 | 11.8 | 11.3 | 11.0 | 9.9 | 9.0 | 8.7 | 8.3 | 8.2 | 8.0 | −2.9 |
| Male hd | 21.9 | 26.5 | 27.2 | 27.6 | 26.4 | 24.4 | 23.7 | 21.2 | 19.1 | 17.6 | 16.9 | 16.4 | 16.1 | −4.4 |
| Female hd | 20.1 | 23.2 | 23.9 | 24.4 | 24.0 | 23.1 | 22.1 | 19.8 | 17.7 | 16.4 | 15.8 | 15.4 | 15.1 | −3.8 |
| Non-family | 12.7 | 14.8 | 14.9 | 14.9 | 15.1 | 14.2 | 14.0 | 12.4 | 11.1 | 10.6 | 10.3 | 10.4 | 10.0 | −3.4 |
| **Race and Ethnicity** | | | | | | | | | | | | | | |
| White | 10.3 | 11.5 | 11.9 | 12.4 | 12.2 | 11.7 | 11.4 | 10.3 | 9.3 | 8.7 | 8.3 | 8.3 | 8.2 | −2.7 |
| Black | 14.8 | 17.5 | 17.8 | 18.3 | 18.1 | 17.2 | 16.5 | 14.4 | 12.6 | 11.6 | 11.3 | 11.2 | 10.5 | −4.9 |
| Asian | 16.4 | 18.9 | 19.4 | 20.3 | 20.2 | 19.2 | 18.1 | 16.1 | 14.4 | 13.6 | 12.9 | 12.0 | 11.3 | −5.2 |
| Hispanic | 34.6 | 42.2 | 42.6 | 42.1 | 40.3 | 38.4 | 37.2 | 33.7 | 30.6 | 29.2 | 27.3 | 26.4 | 25.7 | −4.4 |
| **Nativity** | | | | | | | | | | | | | | |
| Native Born | 8.5 | 9.6 | 10.0 | 10.5 | 10.3 | 9.8 | 9.5 | 8.3 | 7.3 | 6.8 | 6.7 | 6.6 | 6.5 | −3.8 |
| For. Born | 34.5 | 40.0 | 40.5 | 40.7 | 39.7 | 38.1 | 37.0 | 34.1 | 31.2 | 29.8 | 28.2 | 27.5 | 26.8 | −3.5 |
| Benchmark | 12.9 | 14.6 | 14.9 | 15.5 | 15.3 | 14.6 | 14.2 | 12.7 | 11.5 | 10.9 | 10.5 | 10.2 | 10.0 | −3.3 |

All values except in the section on age are given as percent for the non-elderly adult population (aged 18 to 64 years) deprived in at least two indicators. *Hispanic* includes Hispanic, Spanish, and Latinos. *Foreign born* includes naturalized citizens and non-citizens. *Male-headed* denotes male householder with no wife present, *female-headed* denotes female householder with no husband present, and *non-family household* includes male householder not/living alone and female householder not/living alone. Change shows the average annual percentage change in the MPI for each group. Standard errors on each of the MPI values are provided in Table A2 in the Appendix. All values are statistically significantly different from previous year's value at 5% except for those shown with +

**Table 7**  Sensitivity of the multidimensional poverty index to indicator threshold

| Indi | Av | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 |
|------|----|----|----|----|----|----|----|----|----|----|----|----|----|
| 1 | **37.0** | 38.7 | 39.6 | 40.8 | 40.6 | 39.7 | 39.4 | 36.8 | 34.7 | 33.8 | 33.3 | 33.4 | 33.0 |
| 2 | **12.9** | 14.6 | 14.9 | 15.5 | 15.3 | 14.6 | 14.2 | 12.7 | 11.5 | 10.9 | 10.5 | 10.3 | 10.0 |
| 3 | **3.8** | 4.7 | 4.8 | 4.9 | 4.7 | 4.3 | 4.2 | 3.7 | 3.2 | 3.0 | 2.8 | 2.7 | 2.5 |
| 4 | **0.8** | 1.13 | 1.20 | 1.21 | 1.11 | 0.96 | 0.91 | 0.80 | 0.67 | 0.60 | 0.52 | 0.50 | 0.48 |
| 5 | **0.1** | 0.12 | 0.14 | 0.14 | 0.13 | 0.10 | 0.09 | 0.09 | 0.07 | 0.06 | 0.05 | 0.05 | 0.05 |
| 6 | **0.0** | 0.002 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.000 | 0.000 | 0.000 | 0.001 | 0.001 | 0.000 |

Deprived in at least these many indicators. All values are given as percent of the non-elderly adult population (aged 18 to 64 years)

### 4.2 Multidimensional Poverty by Gender and Family Type

There was not much difference in the level of multidimensional poverty by gender, though they had different rates of change over time. During the recession, multidimensional poverty increased among women by 1.6 percent rise per year, whereas it increased significantly by 4.5 percent per year among men. Average MPI was high among single-parent households (around 20 percent) and almost double compared to married couples (around 10 percent). On a positive note, the MPI decreased by almost 4 percent per year for single-parent households in the long-term recovery period.

### 4.3 Multidimensional Poverty by Race, Ethnicity and Nativity

On average, multidimensional poverty rates were least among Whites (10.4 percent), moderately high among Blacks (14.8) and Asians (16.5), and highest among Hispanics (34.7 percent). Previous studies too found a greater incidence of multidimensional poverty among Hispanics.[18] Interestingly, during the recession, the MPI increased only among Whites. In the 11 years, the MPI declined most among Asians (5.2 percent per year on average) and least among Whites (only 2.7 percent per year on average). Importantly, multidimensional poverty was four-times higher among foreign-born individuals (34.5 percent) compared with native-born individuals (about 8.5 percent). Over the decade, the MPI declined by about 3.5 percent per year in each group.

## 5 Sensitivity of Multidimensional Poverty Estimates

Any multidimensional poverty index is based on a set of parameters, such as the indicators used, the weights attached to each indicator, the thresholds and so on. Hence studies measuring these indices typically include a variety of robustness tests.[19] In this section, we

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[18]  See, for example, Dhongde and Haveman (2017), Mitra and Brucker, (2016, 2019), Glassman (2019, 2021); Dhongde and Dong (2022) conduct an in-depth analysis of multidimensional poverty by race and ethnicity.

[19]  See Alkire and Santos (2014), Santos and Villatorro (2018) among others for different types of sensitivity tests.

**Table 8** Multidimensional poverty estimates with modified housing costs

| MPI | Av | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Benchmark | 12.9 | 14.6 | 14.9 | 15.5 | 15.3 | 14.6 | 14.2 | 12.7 | 11.5 | 10.9 | 10.5 | 10.3 | 10.0 |
| Modified | 12.8 | 14.4 | 14.8 | 15.4 | 15.2 | 14.5 | 14.1 | 12.7 | 11.4 | 10.8 | 10.4 | 10.2 | 10.0 |

Deprivation in housing is modified as having severe housing burden and household income is less than $75,000. All values are given as percent of the non-elderly adult population (aged 18 to 64 years)

relax some of the assumptions made while estimating the benchmark MPI and provide the readers a range of possible values of the MPI.

### 5.1 Sensitivity to Threshold Number of Indicators

In the benchmark case, we identified an individual as multidimensional poor if she is deprived in at least two of the six indicators. This cut-off is consistent with the global multidimensional poverty threshold (deprivation in at least 33 percent of indicators) as well as with thresholds used in the literature measuring deprivation in the United States. If we change this threshold, then we are able to see the severity of deprivation in terms of the number of indicators in which individuals were deprived (see Table 7). Suppose we count any individual deprived in at least one indicator as multidimensional poor, then as many as 37 percent of the population is multidimensional poor. Such a low threshold risks identifying all those individuals as multidimensional poor who may choose to be deprived in a given indicator (for instance, choose not to purchase health insurance) and hence tends to overestimate multidimensional poverty. On the other hand, suppose we identify individuals deprived in at least three indicators, then the percentage of multidimensional poor decreases from 12.9 to 3.8 percent. This suggests that most of adults experienced deprivation simultaneously in two indicators; few experienced it in three or more indicators. In fact, there is not much overlap of deprivations beyond three indicators; less than 1 percent of adults were deprived in four or more indicators and less than 0.1 percent were deprived in five or six indicators.

### 5.2 Housing Costs Conditional on Income Levels

In the benchmark case, we consider an individual to be deprived if she has severe housing burden that is monthly owner costs or gross rent in excess of 50 percent of household income. Typically, very few households with income in excess of $100,000 would spend half their income on rent or a mortgage. However, there is evidence that a small percentage of households earning at least $50,000 per year are severely housing burdened, especially if they reside in high-cost neighborhoods in states such as California and New York (Montgomery, 2019). Housing cost is an important indicator in the MPI and is the only indicator among the six indicators that directly uses household income in its calculation. All other indicators are independent of income levels. We now introduce an income threshold while considering housing burden. Suppose we consider only those individuals as deprived in the housing dimension if their household income was less than $75,000 (median annual household income was between $50,000 and $69,000) and had housing costs in excess of 50 percent of their income. We re-estimate the MPI (see Table 8) and find that the proportion
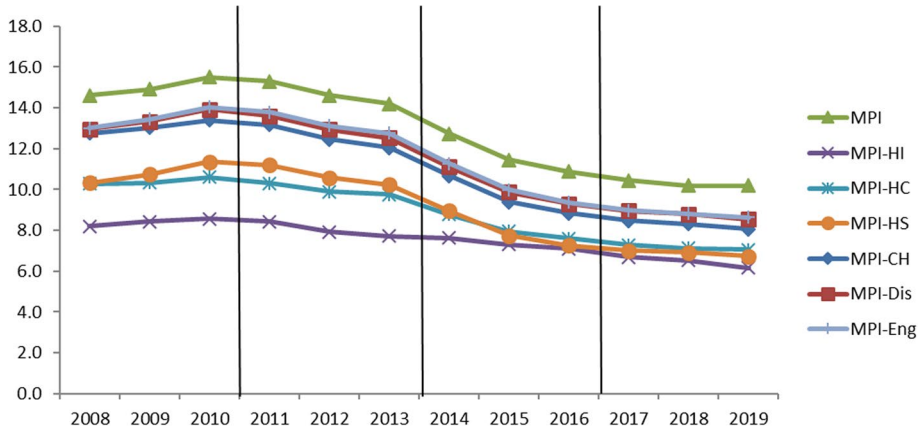
**Fig. 3** Sensitivity of the multidimensional poverty index to exclusion of each indicator. MPI measures deprivation using all six indicators, MPI-HI measures deprivation without health insurance, MPI-HC is without housing costs, MPI-HS is without high school education, MPI-CH is without crowded housing, MPI-Dis is without Disabilities, and MPI-Eng is without English fluency as an indicator. All values are given as percent of the non-elderly adult population (aged 18 to 64 years)

of multidimensional poor, on average, did not vary significantly (it was lower by 0.1 percentage point after the income adjustment to housing costs). Therefore, even when we remove individuals with severe housing burden but having high incomes, we do not see a big change in the MPI estimate. This suggests that the benchmark MPI does not include many households who had high housing costs but also very high incomes.

## 5.3 Sensitivity to Indicator Weights

As seen previously in Fig. 2, the downward trend in the MPI began in 2011, right after the recession, when income poverty rates remained stubbornly stagnant. This downward trend occurred even before any of the ACA provisions went into effect. It is natural to wonder about the impact of the ACA, if any, on multidimensional poverty, since more than 20 percent of the individuals between 2009 and 2014 did not have any health insurance (Fig. 1). The other two indicators with a high incidence of deprivation were severe housing burden and high school incompletion. In the benchmark case, we assigned equal weights to all indicators. Instead, we now assign zero weights alternatively to each of the indicators and re-estimate MPI values. In Fig. 3, we show trends in the MPI when we alternately remove one indicator at a time from the index. Overtime we see that the incidence of multidimensional poverty is the lowest when we remove health insurance as an indicator. The average MPI decreases from 12.9 percent to 7.6 percent (MPI-HI: MPI without health insurance). If we remove housing costs (MPI-HC) or remove high school completion (MPI-HS), then the average MPI is about 9 percent. By 2019, about 6 to 7 percent of individuals were still multidimensional poor, even when we alternatively removed one of the three indicators. Removing each of the other three indicators, namely crowded housing (MPI-CH), disabilities (MPI-Dis) and English fluency (MPI-Eng) alternatively, does not lead to a big change in the value of the MPI to a significant extent. Compared with the benchmark MPI of 12.9 percent, the average value of the MPI on removing any of one of these three indicators is about 11 percent.
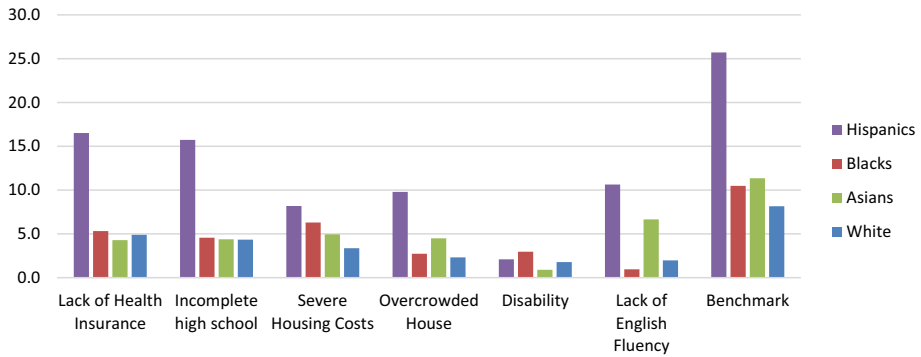
**Fig. 4** Sensitivity of the Multidimensional Poverty Index to Mandating Deprivation in an Indicator. Values in the figure are shown for 2019. Hispanic includes Hispanic, Spanish, and Latinos

**Table 9** Multidimensional poverty estimates by regions

| Regions | Av | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Northeast | 11.0 | 12.0 | 12.1 | 12.7 | 12.8 | 12.2 | 12.1 | 11.2 | 10.2 | 9.7 | 9.2 | 9.0 | 8.7 |
| Midwest | 8.8 | 10.1 | 10.6 | 10.9 | 10.8 | 10.1 | 9.8 | 8.6 | 7.6 | 7.1 | 6.9 | 6.9[+] | 6.6 |
| South | 14.2 | 15.8 | 16.2 | 17.0 | 16.6 | 15.7 | 15.3 | 14.0 | 12.8 | 12.2 | 11.9 | 11.6 | 11.5 |
| West | 15.9 | 18.8 | 19.1 | 19.5 | 19.1 | 18.7 | 18.0 | 15.5 | 13.8 | 12.9 | 12.2 | 12.0 | 11.7 |
| Benchmark | 12.9 | 14.6 | 14.9 | 15.5 | 15.3 | 14.6 | 14.2 | 12.7 | 11.5 | 10.9 | 10.5 | 10.3 | 10.0 |

All values are given as percent of the non-elderly adult population (aged 18 to 64 years). Standard errors on each of the MPI values are provided in Table A2 in the Appendix. All values are statistically significantly different from previous year's value at 5% except for those shown with +

Next, we find out whether certain indicators unduly influence MPI estimates among individuals belonging to a particular race or ethnicity. For example, we test whether the indicator showing a household member with English fluency leads to a greater incidence of Hispanics and/or Asians among multidimensional poor. In order to examine this question, we reassign weights to the indicators such that deprivation in a particular indicator is absolutely necessary in order to qualify as multidimensional deprived.

In Fig. 4, we show estimates of the MPI for the most recent year (2019) using this weighting structure. For example, the first set of bars in Fig. 4, shows MPI estimates when we mandate "having no health insurance" as a required deprivation, the second set of bars shows MPI estimates when we mandate "incomplete high school" as a required deprivation and so on.

The last set shows the benchmark MPI estimates, when all indicators have equal weights. We find that Hispanics had the highest proportion of multidimensional poor population regardless of the alternate weights on different indicators. The only exception is when we assign a greater weight to "having multiple disabilities"; in that case the MPI among Blacks is greater than that among Hispanics. However, "having multiple disabilities" was the only indicator, which if mandated, resulted in less than 5 percent individuals being multidimensional poor among all racial/ethnic groups. Compared with Asians, Blacks had higher MPI values, when health insurance, and housing costs carried more weight. On the other hand, Asians had higher MPI than Blacks when we assigned greater
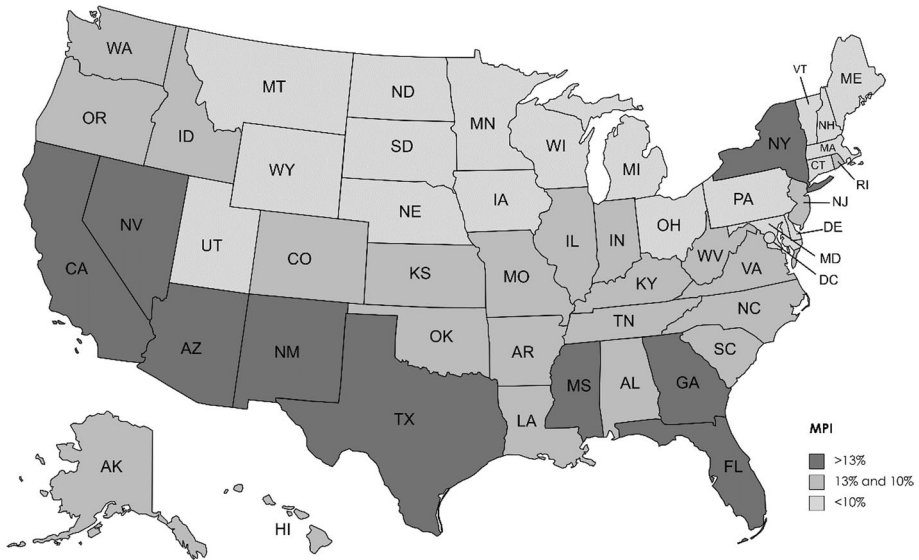
**Fig. 5** Multidimensional Poverty across States. Created with mapchart.net. Colors highlight values averaged over 2008 and 2019 given in Table A3 in the Appendix

weights to "living in an overcrowded house" and "having no household member with fluent English".

## 6 Spatial Variation in Multidimensional Poverty

In this section, we analyze spatial variation in multidimensional poverty. We estimates the MPI in four regions (Table 9). Multidimensional poverty was more concentrated in the South and West, where, on average, more than 14 percent individuals were multidimensional poor over the decade. In 2009, during the Great Recession, almost one in five individuals were multidimensional poor in the West. Even during the recovery following the recession, and as recently as in 2019, the incidence of multidimensional poverty was greater in the South and West compared with the national average. Relatively, the Northeast had lower and the Midwest, the least proportion of multidimensional poor.

### 6.1 Multidimensional Poverty by States

In Fig. 5, we show MPI values for each state, averaged over the decade, and classified in three broad categories. MP values for each state and in each year are provided in Appendix Table A3. As seen in Fig. 5, nine states had MPI values higher than national average (13

percent), most of which were in the South and the West. Twenty-two states had MPI values in a moderate range (between 10 and 13 percent). Finally, 20 states had low incidence (less than 10 percent) and most of these states were in the North and Midwest. Among all states, multidimensional poverty was highest in California and Texas; nearly one in every five adults in these two states were multidimensional poor. Both of these states have a greater percentage of Hispanic populations, a group with overall high levels of multidimensional poverty, as noted previously. At the peak of recession, in 2010, the multidimensional poverty rate was at or above of 20 percent, in California (24 percent), Texas (22 percent) and Florida (20 percent). In the north, New York was an exception, with a high rate of multidimensional poor. On the other hand, some states such as Iowa, Minnesota, North Dakota and Vermont had some of the least (5 to 6 percent) rates of multidimensional poor.

## 6.2 Multidimensional Poverty and Neighborhood Characteristics

There is evidence in the literature that neighborhood characteristics such as air pollution (Mikati et al., 2018), crime rates (Sharkey & Sampson, 2015), lack of recreational facilities (Scott, 2013) are correlated with income poverty. However, previous studies in the U.S. have not examined the link between these factors and multidimensional poverty, largely due to the fact that data on neighborhood characteristics is not collected in the Census' household surveys such as the CPS and the ACS.

Public Use Microdata Areas (PUMAs) are the lowest level of geographical identifiers for individuals and households in the ACS data. PUMAs are areas with population of 100,000 or more. However, PUMAs as geographic identifiers are used only by the Census. Data from other agencies such as the Environmental Protection Agency (EPA), or the United States Department of Agriculture (USDA) is typically available at county level. Unfortunately, there is no one-to-one matching of PUMAs to counties. A PUMA may perfectly overlap a county, or a PUMA may contain multiple counties or a county may contain multiple PUMAs. Hence, we use Census' equivalency files and assign population weighted county values to each of the PUMAs in the ACS.[20] We compile data on six neighborhood indicators at the county level (see Table 10; details on each of the indicators are provided in the Appendix).

We test whether an individual identified as multidimensional poor, is correlated with the neighborhood characteristics that she resided in. Since the dependent variable is binary (1 indicates multidimensional poor, 0 indicates otherwise), we use a logistic regression model (see Table A4 in the Appendix). The estimated coefficients indicate that multidimensional poor tended to live more often in neighborhoods with poor air quality and high crime rates and less so in neighborhoods with recreational facilities.

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[20] PUMAs are non-overlapping contiguous areas and do not cross state boundaries. There is no territory within a state that is not assigned to a PUMA. ACS 2008 to 2011 uses PUMA codes based on 2000 census whereas ACS 2012 to 2017 uses PUMA codes based on 2010 census. We use the cross-walk between PUMA and county provided by the Missouri Census Data Center http://mcdc.missouri.edu/geography/PUMAs.html.

**Table 10** Indicators of neighborhood characteristics

| Indicators | Definition | Source | Mean | Std. Dev | Min–Max |
|---|---|---|---|---|---|
| Air Quality | Average annual concentration of PM2.5 (micrograms per cubic meter) | National Environmental Public Health Tracking | 9.0 | 2.0 | 3 – 19.7 |
| Drinking Water Violation | Violations in one year; 1 if one or more violations, 0 if none | County Health Rankings and Roadmaps | 0.5 | 0.5 | 0–1 |
| Food Environment | Low access to grocery store for low income families and food insecurity | County Health Rankings and Roadmaps | 7.0 | 1.3 | 0–10 |
| Recreation Facilities | Recreation and fitness facilities/1000 population | U.S. Dept. of Agriculture | 0.07 | 0.07 | 0–0.8 |
| Violent Crime | Violent Crimes/ 1000 population | Federal Bureau of Investigation | 2.5 | 2.2 | 0 – 38.8 |
| Property Crime | Property Crimes/ 1000 population | Federal Bureau of Investigation | 19.6 | 12.6 | 0—218 |

(i) We find that violent and property crime rates are highly correlated (0.97), so we combine them and use total crime rate in the regression model. None of the other independent variables have high correlations

# 7 Conclusions

There is a growing interest in measuring multidimensional poverty in the U.S. In the last five years or so, nearly half-a dozen papers and reports have been published on the topic. This paper benefits from the previous literature in many ways. It uses the American Community Survey data and indicators therein which are commonly used in the literature. The paper also contributes to the literature in important ways. It provides estimates of multidimensional poverty over the longest time periods, covering last 12 years. We estimate trends in poverty during the recession and in the short and long-term recovery periods. We also provide, for the first time, trends in regional and statewide estimates of multidimensional poverty over the decade and analyze the relation between an individual's multidimensional poverty status and the neighborhood characteristics in which she/he lives.

We are mindful of the fact that the analysis is not without its limitations. Our choice of indicators is restricted by the availability of data in the ACS. We use not-so-perfect indicators to capture deprivation in some dimensions. Furthermore, we do not have indicators, which are more relevant to measuring multidimensional poverty among children or among the elderly. We assign household values to individuals since we lack data on intra household distribution of resources. In our benchmark index, we assign equal weights to indicators and use standard thresholds such as high school graduation, though we relax some of these assumptions when we conduct a sensitivity analysis. Finally, we estimate multidimensional poverty across states and in our regression analysis, we identify individuals by using PUMAs-the lowest level of geographical identifiers in the ACS data. Although there is no one-on-one matching of PUMAs to counties, it is worth exploring how to use the location information and estimate multidimensional poverty rates at county levels. Thus, these limitations will serve as possible ways for future research to delve deeper into measuring multidimensional poverty in the U.S.

Despite these limitations, we believe that our analysis will be useful for policy purposes. We find that although on average the proportion of multidimensional poor and income poor were similar in size (12 to 13 percent), there was a limited overlap between the two. Only 5.5 percent individuals were both multidimensional poor as well as income poor. Among individuals who were not income poor, deprivation was highest when individuals had incomes just above the poverty threshold. Policies geared specifically towards reducing income poverty preclude those who are not identified as income poor. Yet these individuals suffered multiple deprivations, especially during the recession. In the future, we need policies directed to help not just income poor but also those who are multidimensional poor. Among the multiple indicators of deprivation, having health insurance was an important indicator. At the peak of the recession, more than 21 percent of adults did not have any health insurance, but by 2018, this proportion had decreased to about 12 percent. Multidimensional poverty was much higher among young adults, Hispanics, and foreign-born individuals and was more prevalent in the Southern states compared with the rest of the country. These population groups would most likely have suffered a further setback due to the Covid-19 pandemic. In coming years, as the country recovers from the pandemic, it will be even more important to monitor multidimensional poverty, in conjunction with income poverty in order to get a better idea of the impact on the quality of life experienced by a country's population.

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