

# To Inform or Influence? The Difference between Data Released by Nonprofits and by the Government

Peter F. Orazem  
Iowa State University

Thu Tran  
Iowa State University

Received: 10/04/2019

Accepted: 03/07/2020

## Abstract

Nonprofit organizations have become increasingly engaged in disseminating information. Unlike federal statistics that are collected with rigidly proscribed procedures, nonprofits have an advocacy role that may influence the information they release and the interpretations they derive from that data. While federal statistics are released to inform opinion, nonprofit statistics are released to influence opinion. Using as cases the Feeding America county food insecurity statistics, the United Way ALICE estimates of working poor, and the *MIT Living Wage Calculator*, we show how the desire to influence policy can lead nonprofits to release data characterized by flawed methodology and misleading or implausible values. Because errors or biases in federal data have been widely researched and publicized through peer review, users can adjust to the known noise in the data. Flaws in data reported by the nonprofits are not made transparent, and so users will make bad decisions if they assume the information is correct.

## 1 Introduction

The U.S. federal statistical agencies produce a wealth of information on the country's social, economic and demographic characteristics. Advances in computational power and information science have allowed rapid expansion of the types of information available. Consistent and careful measurement following set procedures insures that the data are reported in ways that are transparent and easily understood. While reported data on poverty rates, unemployment, or prices may be subject to errors, knowledge of the properties of the public data allow adjustments so that the targeting and resource allocation can be improved.

The government's motives for providing data differ from a nonprofit's motives for releasing information. The government strives to use well-known and professionally validated methods to collect and disseminate their data but it does not have a vested interest in the values themselves. The nonprofits are interested in producing and disseminating data that support their causes. Data that does not support the cause will not be released. Moreover, nonprofits have typically presented their information without discussions of possible errors or biases. Estimates are presented as fact. Casual consumers of information may not be able to distinguish between data generated by the government or the nonprofit and may view both as equally valid.

This study shows several prominent examples of how data have been used improperly to misappropriate or mislead. In particular, we show

1. How high local poverty rates may not imply high local poverty;
2. How low local household incomes may not imply low local family incomes;
3. How high local food insecurity rates may not imply high levels of food insecurity;

4. How high rates of working poor may be uncorrelated with true rates of working poor;
5. How measures of living wages based on presumed minimum expenditures on necessities are actually consistent with expenditures of households in the upper quartile of incomes.

The first two cases relate to government provided data. We show how places that have high proportions of young adults will look artificially poor in the government statistics. Anti-poverty programs whose targeting is based on poverty or household income will incorrectly benefit some wealthy communities. However, because the flaws in the government data are made public, the targeting could be easily improved using adjustments that are also reported by the government. The last three cases all involve nonprofit groups that allege that federal data do not adequately measure poverty or food insecurity. These data are not presented with accompanying precautions and are more likely to mislead.<sup>1</sup>

We begin our analysis by first showing why government data is likely to be more reliable than data provided by a nonprofit. We then illustrate how government data, even when subject to errors, can be adjusted because the properties of the data are known. In the three examples of data reported by nonprofits, the mistakes in the data are not transparent and data users are more likely to be misled.

## 2 Why would public provision of information be more reliable?

There are several reasons to give more credence to government data. As a public good whose collection is subject to returns to scale, a single data supplier can provide the optimal information at the lowest cost. The data would be undersupplied by private suppliers. However, the great value the market places on information also creates an incentive for a private supplier to manipulate outcomes for its private advantage. If data were supplied by a nonprofit, the data would be released strategically to meet the objectives of the nonprofit rather than following scientific objectivity.

### 2.1 Public goods, private uses, and the value of coordination

Government information has great value. Hughes-Cromwick and Coronado (2019) present an interesting review of the business users of federal data. The heaviest users are in insurance, finance, banking and real estate. The government data intensive sector included 2.7 million employees by 2015. The most important data for these private users were employment, unemployment, prices, wages, GDP, population, and income.<sup>2</sup> As there is obvious private value to accessing this data, it is natural to ask what would be the likely outcome if this data were not freely available to the public.

Absent the public option, there would be an incentive for private agents to collect the data. Agents who incur costs acquiring the information would want to keep the information private to produce monopoly rents on the information. Presuming returns on data use would be greater than the competitive norm, there would be competing data acquisition firms collecting the same information. Spreading the data collection across multiple firms leads to costly duplication of effort. As a result, the same amount spent privately across multiple agents on data collection as is currently spent publicly by the government would result in noisier data.

If the agents decide to make the data public, as is true of the information provided by nonprofits in our case analyses, then we know there will also be noisier data. If data is a public good, it is most efficient for it to be provided by the government. Private providers of a true public good will supply less than the optimal amount of the good due to free rider incentives. Federal collection and dissemination of data can provide the critical coordination and resources necessary to provide the socially efficient level of public data (Jarmin, 2019).

---

<sup>1</sup>Our context is the United States. As noted by a referee, there are many examples of government data that are biased to support government objectives such as the agricultural production data released by the Soviet Union and the inflation rates released by Argentine statisticians. We would expect our analysis would carry over to the quality of data released by the OECD countries where international standards on measurement govern information collection and dissemination.

<sup>2</sup>This was based on responses to a survey of members of the National Association for Business Economics.

But the more serious concern with privately provided data of this type is that private agents have a vested interest in the outcomes. Because contracts conditioned on the realized outcomes of employment, prices, income or unemployment data, there is an incentive for the data provider to profit from prior knowledge of the results (Jarmin, 2019). But even more concerning is the possibility that the announced realizations of the variables will be biased in favor of the interests of the agent collecting and releasing the data. The reason publicly provided data produced under strict rules governing data collection, dissemination and timing of release can be used to index bonds, inform futures markets, and adjust labor contracts is that the entity collecting the data has no vested interest in the realized outcome. Having a disinterested government agency collecting the data makes the information more valuable to the private sector.

For nonprofits who are producing publicly available information, one has to ask the same questions that one would ask when a for-profit firm provides public data: what is the incentive to allocate scarce resources to disseminating this data? The data must support the mission of the nonprofit, and so the nonprofit is not indifferent to the realizations of the measures it releases.

## 2.2 Providing data for interpretation versus providing interpretation: The IRS and the CPI

It is common for scholars to generate different conclusions from the same data. For example, using Internal Revenue Service (IRS) data, Piketty et al. (2018) found that pretax income share for the top 1% rose 7.6 percentage points since 1960, while after-tax income shares rose 5.6 percentage points. In a reassessment, also using IRS data, Auten and Splinter (2017) placed the income share growth for the top 1% at 2.8 and 0.3 percentage points, respectively. The differences in the conclusions are driven by assumptions about unobservables. For example, 38% of the differences in 1% income share are due to an assumption by Piketty et al that allocates 50% of underreported income to the top 1% while, using tax audit data, Auten and Splinter found that only 15% should go to the top 1%. The entire difference between the two papers in assigning after-tax income shares is explained by Auten and Splinter's assumption that government consumption should be treated partially as a public good that is shared equally across income groups as opposed to the Piketty et al assumption that all government consumption is a private good with consumption shares matching income shares. What matters for our study is that the disagreement in conclusions is not driven by the data provided by the government, but by the interpretation by users who understand the properties of the data.

Our focus is on the summary information the government releases from raw data. One of the most prominent examples is the Consumer Price Index (CPI). The Bureau of Labor Statistics reports the rate of inflation based on prices it collects on thousands of commodities in various metropolitan areas every month. Over its over 100-year history, numerous economists including several Nobel Laureates have proposed alternative indexes that are more consistent with underlying consumer theory. Committees of elite economists have researched the potential biases in the CPI and suggested improvements including efforts to adjust for changing product quality, incorporating new products, and accommodating substitution toward goods with slower price increases. Various sources of bias can cause the CPI to overstate the true cost of living (Hausman, 2003). Abraham (2003) and Jarmin (2019) review some of the implemented and proposed changes, including some designed to correct for declining response rates to surveys, efforts to incorporate administrative data, and even strategies to incorporate price information obtained from online sources (Cavallo and Rigobon, 2016).

The true mark of the trust in the CPI is that market agents will alter their valuation of stock prices and exchange rates in response to its release. Labor contracts, social security payments and indexed bonds are pegged to its value. The possible flaws in the CPI do not mislead because the flaws are in the open for all to see. Because the CPI is so transparently collected and produced, and because its properties so carefully researched, it is possible for users to interpret its value and to adjust for possible bias if they wish. In contrast, the nonprofits provide the interpretation.

### 2.3 The missions to inform versus influence public opinion

We can document the differences in motivation for disseminating information between nonprofits and government agencies by referencing their mission statements. The Census Bureau states that its mission is, “to serve as the nation’s leading provider of quality data about its people and economy... We are guided on this mission by scientific objectivity, our strong and capable workforce, our devotion to research-based innovation, and our abiding commitment to our customers.”<sup>3</sup> The United Way Alice Study claims that its mission is , “to make the invisible visible by shining a light on the true number of families struggling in the U.S.. Our new metrics offer a better way to count and understand ALICE, and to ultimately inform policy decisions to affect positive change for this growing portion of our population. Armed with this data, we aim to change the national dialogue about the impact on families, communities, and all of us.”<sup>4</sup> Feeding America says that it releases its food insecurity data at the county and congressional district level to demonstrate that food insecurity is found everywhere, and that, “food banks, partner agencies, policy makers, business leaders, community activists and concerned citizens will use this information to fully engage in the fight against hunger.”<sup>5</sup> The *MIT Living Wage Calculator* does not list a mission statement, but its developer said it was built, “to argue that the minimum wage was insufficient to raise a family. Wages are 20 years out of date, and the people who babysit your children or wash your car or mow your grass are not making enough money to make ends meet.”<sup>6</sup> All of the nonprofits stated that they hoped the data would influence policy in the direction that would meet their objectives. As we will see, the data they release is biased toward their desired policy objectives. In contrast, the Census says it is focusing on data quality and scientific objectivity, and its data is not designed to sway a policy debate.

While government agencies subject their data to scientific scrutiny through peer review, nonprofits want their data to influence public opinion. As a result, the primary audience for their information is the media. And while government data is subjected to rational skepticism, the media presents the data provided by nonprofits without mention of possible bias. As an example, the United Way Alice web page lists 97 news stories using their information since 2017 with headlines such as Half of Dallas households are struggling to make ends meet (Dallas Morning News), . Almost half of US families can’t afford basics like rent and food (CNN Money), and Half of Philadelphia households struggle to make ends meet (WNYX Philadelphia). Not one of the 97 suggests the data may be unreliable.

## 3 Government Data Case 1: How local poverty rates can target poverty relief toward the rich

The U.S. is one of the few countries in the world that produces an official poverty rate. Mollie Orshansky’s original measure of 3 times the minimum amount necessary to provide nutrition for a family of four was developed because the U.S. was embarking on the War on Poverty but lacked a measure of poverty. Since then, the official poverty-level income is the original Orshansky measure correcting for inflation. Equivalence scales are used to adjust for family size and age.

The federal poverty statistics are frequently used to evaluate the spatial distribution of poverty (Lewis Jr and Johnson, 2018). Poverty rates persist over time (Partridge and Rickman, 2008), which has been argued to support place-based economic interventions aimed at high poverty rate locations (Partridge et al., 2015). However, poverty rates are not adjusted for local prices, and so the cut-off income levels will imply higher real incomes in places with low living costs. Wages and incomes adjust to costs of living at least partially if not completely (DuMond et al., 1999; Winters et al., 2009), and so incomes will be lower in places with low living costs. As a result, the pattern of rising poverty rates as distance from metropolitan markets increases (Weber, 2007; Partridge and Rickman, 2008) may be a consequence of the constant poverty income threshold imposed on areas with lower nominal incomes, even if real incomes are not different.<sup>7</sup>

<sup>3</sup><https://www.census.gov/about/what/census-at-a-glance.html#mission>.

<sup>4</sup><https://www.unitedforalice.org/home>.

<sup>5</sup><https://www.feedingamerica.org/research/map-the-meal-gap/by-county>.

<sup>6</sup>Brown (2015) <http://news.mit.edu/2015/building-living-wage-calculator-amy-glasmeier-0807>.

<sup>7</sup>This implies that persistently high rural poverty rates may be a result of persistently low cost of living and not actual poverty (Jolliffe, 2003), due largely to the much lower cost of rural housing (Kilkenny, 2010). The stronger evidence of persistent

While the flaws in the U.S. poverty rate are widely known, it is an important statistic used to qualify for numerous individual and community transfer programs (Hotchkiss and Phelan, 2017).<sup>8</sup> Neighborhoods and communities with atypically high poverty rates can be in line for Community Development Block Grants, school nutrition programs, Head Start, Home Energy Assistance, and many others. The 2017 Tax Cut and Jobs Act offers tax incentives for developments in opportunity zones, areas with poverty rates above 20%. How well these programs reach the targeted poor depends on the extent to which the poverty rate reflects true poverty across communities.

As shown in Table 1, poverty rates differ by age, with the highest poverty rates for those aged 18-24. The reason is that this group is atypically leaving homes where the householders were at or near the peak of their earning and establishing a household with earnings at the bottom of the age earnings profile. Moreover, a disproportionate share of the 18-24 year-olds are engaged in schooling rather than income generating activities. Most college students who rely on their family for resources are considered poor based on their own incomes, even if their true access to resources would not have qualified them as poor when residing at home. Cities that have large fractions of the population aged 18-24 will appear poor according to the federal criteria, even if the 18-24 year-olds are not really atypically disadvantaged in terms of consumption or access to resources.

Table 1: Poverty Rates, overall and by age groups, state and land grant counties, 2013-2017

Panel A	United States	State	Land Grant County
6 to 11 years:	20.7%	19.1%	16.9%
12 to 17 years:	18.1%	16.7%	13.3%
18 to 24 years:	24.8%	23.8%	51.9%
25 to 34 years:	15.2%	14.2%	16.3%
35 to 44 years:	12.0%	11.4%	10.1%
45 to 54 years:	10.3%	9.9%	8.3%
55 to 64 years:	9.6%	9.8%	7.4%
65 to 74 years:	8.4%	8.0%	5.6%
75 years and over:	10.7%	10.1%	8.0%
Share of population aged 18-24	9.2%	9.7%	18.9%
Overall poverty rate	14.9%	14.1%	17.5%
Poverty rate excluding ages 18-24	13.9%	11.9%	10.2%
Panel B: Land Grant County Poverty Rate > State Avg.			
All ages	70.8%		
Excluding ages 18-24	16.7%		

Source: American Community Survey.

Table 1 reports average poverty rates for counties housing land-grant universities compared to their states and the U.S. average. Land-grant counties are atypically poor using federal statistics. The reason is that these counties have population shares aged 18-24 that are about double the average for their states and the U.S. as a whole. Moreover, the 18-24 year-olds in land-grant counties are more than twice as likely to be considered poor as are 18-24 year-olds generally because the other young men and women are working and not in school. Because of their high rates of measured poverty, land-grant counties qualify for numerous programs aimed at combating poverty. Virtually every land-grant county will have student-intensive census tracts that qualify for the opportunity zone tax credits. However, other than the 18-24 year-olds, land-grant

differences in local labor demand comes from lagged responses of unemployment rates (as reviewed by Partridge et al. (2015), or employment rates (Amior and Manning, 2018) to economic shocks, leading to persistent differences in unemployment and employment rates across communities. While commuting helps spread the benefits of higher wage in cities to the surrounding rural areas (Ganning et al., 2013), more remote rural areas outside commuting distance do not get spillovers from urban economic growth.

<sup>8</sup>See Blank (2008) for a review of the problems with the measure and possible alternative measures.

counties are less poor than the rest of their states or the U.S. as a whole. Other college towns, but also the fastest growing cities similarly attract high proportions of 18-24 year-olds and will have overall poverty rates that do not reflect the low poverty status of the other age groups.

Because the attributes of the federal poverty rates are well known, it is possible to adjust the qualification criteria to remove the bias in favor of poverty alleviation funding available for college towns. Excluding 18-24-year-olds from the poverty major would level the playing field for targeted poverty relief programs.

## 4 Government Data Case 2: How household income misleads inference about family income

The U.S. Census divides households into families (at least two related individuals living in the same domicile) and nonfamily households. Unrelated individuals residing together are considered a nonfamily household. Young unrelated adults, whether working or students, are the most likely to form nonfamily households. The average earnings for nonfamily households are much lower than average earnings for family households, as shown in Table 2. Median earnings for family households were \$75 thousand in 2013-2017, more than double the median for non-family households. The difference is even larger in land-grant counties. In addition, a smaller share of households in land-grant counties are family households. As a result, even though median family incomes are higher in land-grant counties, the median household income is lower than the median for the state as a whole.

Table 2: Family and household income for selected United Way states, 2013-2017

Variable	Households		Families		Ratio: family to nonfamily household income	Share of households that are families
	All	Non-family	All	Married couple		
State	\$ 60,474	\$35,885	\$75,020	\$89,715	2.09	0.65
Land Grant	\$ 58,627	\$33,757	\$79,985	\$94,219	2.37	0.58

Source: American Community Survey. Note: Across land-grant counties, the correlation between the ratio of household income and the share of households that are families is 0.87.

The U.S. Bureau of the Census reported that real median household income rose 0.9% in 2018, a gain that was not significantly different from zero. At the same time, the poverty rate fell to its lowest level in 17 years and real earnings rose 3.4%. According to the *New York Times*, “Census officials said they could not readily identify the cause [of the stalled income growth].<sup>9</sup> In fact, the Census’ next bullet point on their press release reported that real family household income rose 1.2% and real nonfamily household income rose 2.4% with both changes being statistically significant. The reason household income grew more slowly than did the incomes of the two subcomponents of household income is that the number of nonfamily households rose 2.2% while the number of family households did not change. When the economy is strong, young adults leave their parents and form new low-income households. As a result, median income across all households grows more slowly than the incomes of both family and nonfamily households.<sup>10</sup>

In general, counties with high shares of family households among all households will have high average household incomes, regardless of whether the family or nonfamily households are relatively well off compared to their peers. The correlation between the share of family households and median household income across land-grant counties is 0.87. As a result, counties with large shares of young, single adults will seem poorer than they are. Because young adults have left rural areas and the young have concentrated in urban and metropolitan areas, average household income will be artificially high in rural areas and low in metro areas compared to their true economic circumstances. Because this bias is known, it is simple to remove the bias by comparing cities on family income or by focusing on households aged over 25 years.

<sup>9</sup>Reuters. “Ahead of Election Year, More Americans Lack Health Insurance, Incomes Stall.” *New York Times*, September 10, 2019.

<sup>10</sup>Among other papers, the *Washington Post*, the *Los Angeles Times* and the *Wall Street Journal* all prominently cited the lack of significant growth in household income without noting the increase in the subcomponents.

## 5 Nonprofit Data Case 1: How some of the highest food insecurity rates are allocated to counties with low food insecurity

Food-insecure households are defined as those that, at some time during the year, had difficulty providing enough food due to a lack of resources. Food insecurity measures are based on questions added annually to the December Current Population Survey (CPS). The CPS sample of about 50 thousand households is not considered sufficiently large to provide reliable information on local food insecurity. As a result, the USDA only reports food insecurity at the state level.<sup>11</sup>

The group Feeding America reports county-level food insecurity measures in their Map the Meal Gap, using a procedure developed by Gundersen et al. (2017). In essence, this strategy allocates state-level food insecurity to the counties in the state using information on state-level income and demographics. The procedure estimates an equation of the form

$$FL_{st} = \alpha_0 + \alpha_u U_{st} + \alpha_p P_{st} + \alpha_Y Y_{st} + \alpha_O O_{st} + \alpha_D D_{st} + \varepsilon_t + \varepsilon_s + \varepsilon_{st} \quad (1)$$

where  $FL_{st}$  is the state  $s$  food insecurity rate in year  $t$ ,  $U_{st}$  is the unemployment rate,  $P_{st}$  is the poverty rate,  $Y_{st}$  is the median income,  $O_{st}$  is the fraction living in owned rather than rented housing,  $D_{st}$  is a vector of demographic measures, and  $\varepsilon_t$  and  $\varepsilon_s$  are time and state fixed effects. The authors then apply the same coefficients to county data to generate county-level measures.

The only way this procedure is accurate is if the same coefficients that apply to the state level in (1) apply to all the counties in the state. That would only be true if income and poverty are measured equivalently in urban and rural places and in places with older and younger populations. As noted above, rural poverty rates are exaggerated because the income threshold is not adjusted for differences in local cost of living. Rural incomes are low reflecting the lower living costs. Both will generate artificially high projected rural county food insecurity rates. In fact, Gundersen et al. (2017) report rising food insecurity as counties become more rural.<sup>12</sup> Gundersen (2019) reports substantial heterogeneity in food insecurity across counties. Gundersen et al. (2018, Appendix B Table) presents a listing of counties with the greatest change in food insecurity. But none of these conclusions is due to actual observations of food insecurity. Instead, they are based on projected food insecurity based on the underlying heterogeneity in measured county poverty rates, nominal incomes, and demographics. There is no way to know if these conclusions are actually true.

Table 3: Reported food insecurity rates by state and land grant county, overall and for children

Variable	Land Grant County		State	
	All ages	Children 0-17	All ages	Children 0-17
Food insecurity rate	14.1%	16.6%	12.6%	17.6%
Correlation with the fraction of population aged 18-24	0.63	-0.08	-0.14	-0.24

Source: Authors' calculations using data from Gundersen, Craig, Adam Dewey, Michael Kato, Amy S. Crumbaugh and Mark Strayer. 2019 and the U.S. Bureau of the Census.

We can show that the method generates obviously inflated food insecurity rates for college towns. The inflated poverty rates in land-grant counties due to high fractions of 18-24 year-olds in the population result in inflated allocated food insecurity rates. All the land-grant counties in the Midwest including the authors' home base in Champaign-Urbana have atypically high food insecurity rates. The only county in Iowa deemed to have atypically high food insecurity is Story County, home of Iowa State University. As shown in Table 3, allocated food insecurity rates in land-grant counties are higher than in their states. On the other and, food insecurity rates for children under 18 are lower in the land-grant counties than in their states. The higher

<sup>11</sup>Coleman-Jensen et al. (2019) provide a summary of the 2018 food security estimates.

<sup>12</sup>The county food insecurity measures have been used to argue that 79% of the most food insecure counties are rural counties. This is entirely due to the lower incomes and higher poverty rates in rural counties that may just reflect the lower living costs in rural areas. The Feeding America studies have no direct information on rural food insecurity.

the fraction of the population aged 18-24 in land grant counties, the greater their allocated food insecurity rates, even though the correlation between 18-24 year-olds and food insecurity is negative in the state as a whole. Moreover, if the assigned food insecurity rates are inaccurate for college towns, they are inaccurate in less predictable ways for all counties. We just have no way of knowing which numbers are too large or too small, as the errors or biases in the data are not defined.

## 6 Nonprofit Data Case 2: How the United Way ALICE reports distort information on struggling families

Starting with a pilot project in New Jersey in 2009, the United Way initiated a series of commissioned studies to establish the number of working poor (ALICE) households by county in each of 18 participating states.<sup>13</sup> The ALICE Project asserts that the Federal Poverty Level does not accurately measure the true level of need. Instead, it seeks to provide estimates of the fraction of households that cannot meet a “bare-bones household budget composed of the amount required for minimal housing, childcare, food, transportation, health care, technology and taxes. The study reports a Household Survival Budget (HSB) for each county, and then compares that to measures of household incomes in the county.

The validity of this exercise requires both accurate measures of the required budget for necessities and accurate measures of household income. Neither of these conditions are satisfied. To begin, 22% of the survival budget is allocated to childcare! The reason is that the study assumes poor households send their children to registered day care providers and pay full price. Unregistered day care costs half that amount, and both public and private programs help to subsidize day care costs for poor families. The day care cost estimate is what middle- or upper-class families would pay.

The ALICE study assumes that health insurance represents 15% of the survival budget. However, 68% of households with incomes under \$25 thousand receive publicly provided health insurance and pay little or nothing. For households between \$25-50 thousand, 53% receive publicly provided insurance. As a result, the study exaggerates what poor households pay for health insurance.

Food costs are assumed to be the thrifty food budget defined by the USDA, a reasonable assumption. However, the rest of the expenditures are assumed to be near or at the average across households, and the average household is not poor. The study assumes that housing costs for the poor are at the 40th or 50th percentile rents in the market. By definition, these would be the rents paid by households in the middle of the income distribution. Transportation costs and technology costs are also based on average expenditures. In short, most of the survival budget is set by budgets reflective of the population average.

Based on these budgets, the United Way ALICE reports generate an amount deemed to be the minimum necessary for a family to survive. The numbers are astounding. For a family of two adults and two preschool children, the household must earn a minimum of from \$54 thousand in Louisiana to \$78 thousand in Connecticut! The study then computes the fraction of households with incomes below the HSB threshold. Rather than using family incomes, however, the ALICE studies use household incomes in making the comparisons. That is clearly a mismatch in that the estimated minimum budgets are clearly oriented to family expenditures.

The result is an unbelievable fraction of households that are deemed unable to meet their minimal needs to survive. As shown in Table 4, from 37% to 50% of households cannot meet a bare bones budget for survival, depending on the state. Despite being among the richest counties in their states based on family household income, the fraction of land-grant county households that fall below the ALICE threshold is higher than the state average in 10 of 16 cases for which we could obtain the data. The apparent poverty of college towns is entirely due to artificially low household incomes because of the high fraction of 18-24 year-olds whose required necessities have little to do with the ALICE study assumptions. The mismatch between family costs on the one hand and nonfamily household income on the other is driving the high rates of estimated working poor.

The ALICE studies mention no potential biases in their reported estimates of the working poor. Of the

---

<sup>13</sup>ALICE® is an acronym for Asset Limited, Income Constrained, Employed. All state reports are available at <https://www.unitedforalice.org/>

Table 4: United Way estimate of ‘ALICE’ households as a percent of all households, land grant counties and state estimate, various states

State	Land Grant County	State
Connecticut	33%	40%
Florida	50%	46%
Idaho	49%	40%
Indiana	42%	39%
Iowa	42%	37%
Louisiana	39%	41%
Maryland	43%	38%
New Jersey	35%	39%
New York	50%	45%
Ohio	40%	42%
Oregon	42%	41%
Rhode Island	42%	42%
Texas	51%	42%
Virginia	39%	50%
Washington	52%	37%
Wisconsin	45%	38%
Average	43.3%	41%

Source: ALICE studies, various states.  
<https://www.unitedforalice.org/all-reports>. Note: Correlation between ALICE percentage and population share aged 18-24 is 0.55.

192 national and regional media articles cited on their web site, not a single one mentions any concerns about these implausibly high percentages of households deemed unable to meet their basic needs.<sup>14</sup>

## 7 Nonprofit Case 3: Why the minimum living wage budgets require upper class family incomes

The ALICE Household Survival Budget is an example of the living wage budget analysis commonly used to establish minimum wages or incomes necessary to meet budget needs. There is a relatively limited literature on living wages, and most of the focus of that literature has been on the employment and wage effects of implementation (Adams and Neumark, 2005) or on the philosophical underpinnings of the policy (Werner and Lim, 2016). Little attention is paid to whether the living wage budget itself is a reliable estimate of the amount necessary for subsistence.

If the Living Wage budgets are accurate, they should correspond to the actual spending patterns observed for households. Because the ALICE studies are only available for a subset of states, we will conduct the comparison using the *MIT Living Wage Calculator* that uses a methodology similar to that used to compute the ALICE Household Survival Budget but is nationally representative (Nadeau, 2018).

We report the distribution of expenditures on the necessities defined by the *MIT Living Wage Calculator* to the actual distribution for a family of four using the Bureau of Labor Statistics’ Consumer Expenditure Survey (CES). We report the results in Panel A of Table 5. The median amount spent on necessities in the CES is \$69 thousand compared to the MIT amount of \$67 thousand, and so the amounts are in the same ballpark. However, the MIT assumptions about budget shares are not at all similar to how households actually spend their money. MIT assumes that households devote almost 20% of their budget to childcare, but the actual share is only 3.2%. The MIT study also overstates budget shares for food, health and transportation, but the actual expenditure shares on housing and other necessities in the CES are much

<sup>14</sup><https://www.unitedforalice.org/in-the-news/categories/national-media>.

larger than presumed by the *MIT Living Wage Calculator*. The *MIT Living Wage Calculator* has little in common with how people actually allocate their budgets.

Table 5: Household expenditures on necessities in 2017: Summaries of the Survey of Consumer Expenditures (SCE) and the MIT Living Wage Calculator

Expenses on Necessities	Expenses on Necessities	Share of Expenditures on Necessities					
		Health	Food	Daycare	Trans.	Housing	Other
Median SCE	\$69,230	7.6%	14.6%	3.2%	16.6%	31.0%	27.0%
MIT Living Wage	\$67,146	12.0%	16.8%	19.8%	19.3%	21.6%	10.5%

Panel B: Distribution of amount spent on necessities by household type							
	MIT Living Wage	Survey of Consumer Expenditure					
		Average	10%	25%	50%	75%	90%
Single parent, at least 1 child	\$51,969	\$43,483	\$17,440	\$24,135	\$36,514	\$54,275	\$80,529
Couple with kids	\$60,463	\$72,587	\$28,873	\$41,142	\$60,237	\$88,347	\$123,521
Family with 2 kids, 2 working adults	\$67,146	\$81,080	\$34,050	\$48,692	\$69,230	\$99,700	\$129,165

Source: Nadeau and Glasmeier (2019) and authors' computations using the 4 quarters of the 2017 Survey of Consumer Expenditures (SCE). All values use household weights.

The fundamental flaw in the ALICE and MIT studies is the presumption that expenditure on necessities are independent of income. In fact, households vary their expenditures on necessities as their incomes rise as would be true of any normal good. Poorer households moderate their expenditures while richer households spend more. For example, poorer households eat more hamburger while richer households eat more steak.

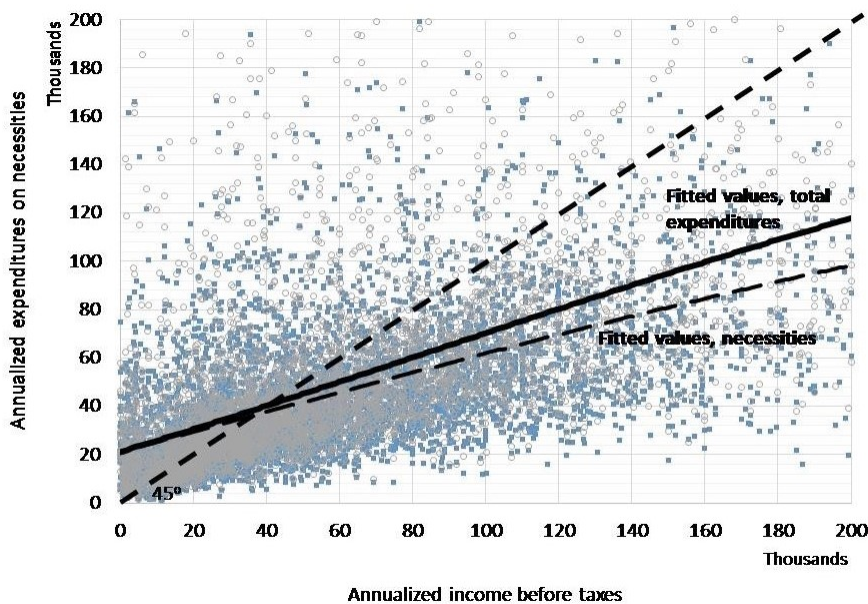
Figure 1 shows the scatter plot of expenditures on necessities against household income. We also show the 45 degree line where expenditures equal income. If households spent every dollar they earned, expenditures would rise dollar for dollar along the 45 degree line. In fact, few households spend exactly what they earn.

The poorest households spend more on necessities than they do on income because they receive in-kind benefits of insurance, housing, and food. As a result, the average expenditure line lies above the 45 degree line at the lowest incomes. By the time income reaches \$35 thousand per year, average expenditures on necessities are equal to average income. Thereafter, as income continues to grow, expenditures on necessities grow more slowly than overall expenditures. In addition, at incomes above \$35 thousand, households start purchasing luxuries and start to save. Neither of these behaviors are consistent with the *MIT Living Wage Calculator* contention that the minimum survival budget average \$67 thousand. If that were true, no households could purchase luxuries or save until their incomes rose above \$67 thousand. In Figure 1, households with pre tax incomes of \$67 thousand spent an average of \$4 thousand on luxuries and saved almost \$17 thousand per year.

There is tremendous variation in expenditures on necessities, even for households with the same incomes. Families with four persons earning \$25 thousand, roughly the poverty level in 2017, had expenditures on necessities ranging from \$12 thousand to \$105 thousand. The distribution of expenditures on necessities by household type are summarized in Panel B of Table 5. For a family of four, the 10th percentile expenditure on necessities is \$34 thousand and the 25th percentile is \$49 thousand. Clearly many households spend much less than the presumed minimum level necessary for survival. In fact, single parent households spending at the presumed minimum survival level are spending at the 75th percentile of all households.

The assumptions underlying the *MIT Living Wage Calculator* minimum budget are similar to those in the ALICE study – that households need to spend the average amount on transportation, housing, insurance,

Figure 1: Expenditures on necessities and household income for four person families with two adults



childcare, and other necessities. However, the average household in the United States is not poor, and the average household increases its spending on necessities as its income rises. As a result, the highest income areas have the highest required Living Wage as computed by MIT. For a family of four, the living wage varies from a low of \$64 thousand in the Midwest and South to \$72 thousand in the North, reflecting the average incomes in those places. The reason you need a middle-class income to meet the ALICE Household Survival Budget or the *MIT Living Wage Calculator* budget is that the budget reflects middle class expenditures.

Another way of illustrating how poorly the ALICE Household Survival Budget or the *MIT Living Wage Calculator* budget reflect the needed expenditures of the poor is to look at what the incomes are of households who actually spend their required amount on necessities. As reported in Table 6, the average income of households spending between \$64 - \$72 thousand on necessities is \$118 thousand for households with at least one working adult and \$125 thousand for households with two working adults. In other words, in order for households to spend on necessities at the level predicted by ALICE or MIT to attain minimal survival, they would have incomes in the upper quartile of all households in the United States.

Table 6: Average household income for four-person households with expenditures on necessities between \$64,025 - \$72,329

	Before Tax	After Tax
Couple with kids	\$117,678	\$101,896
Family with 2 kids, 2 working adults	\$125,192	\$107,421

Source: Income Data is the weighted average across the four quarters of the 2017 Survey of Consumer Finances. The range of expenditures on necessities is the range of minimum necessary expenditures reported by the MIT Living Wage Calculator for the North, South, Midwest and West (Nadeau and Glasmeier, 2019).

As noted above, Living Wage studies do not seem to question the validity of the minimum budgets. Werner and Lim (2016) review reported that living wages were typically set well below the estimated subsistence budgets, but concluded that the living wages were set too low. They did not consider that the estimated budgets might overpredict minimum incomes. Phillips (2011) argues that subjects in medical research should

be paid more than the minimum wage as that is an exploitative level, but not as much as the average wage for production workers because that would be an undue inducement. Instead, citing the MIT Living Wage study, she proposes paying that level because they represent a, “minimum estimate of the cost of living for low-wage families.” Ironically, the MIT Living Wage is well above the average paid to production workers.

## 8 Conclusions

Nonprofit organizations rely on motivated donors. Donors are increasingly educated and increasingly concerned about evidence that resources are allocated effectively and to the truly needy. Armed with more powerful statistical tools and more easily available data, nonprofit agencies can tailor their information dissemination in ways that support their advocacy positions. Indeed, their stated motivation for releasing the data is to support policies consistent with their charitable aims. Feeding America wants to show that hunger is everywhere, and so they disaggregate state-level data on food insecurity to the county-level using a flawed methodology. They then report that 79% of the most food insecure counties are rural, even though the original data does not indicate whether respondents are rural. The United Way wants its data to support a view of substantial need, even among households that work. They then use a method that compares family expenditures against nonfamily household incomes that generates an artificially large share of ALICE households. The *MIT Living Wage Calculator* is aimed at supporting significant increases in the minimum wage. They use a methodology that defines middle-to-upper class expenditures on necessities as the bare-bones budget level, yielding implausibly high incomes necessary to survive.

The examples we present are not atypical of a rising tendency for advocacy groups to advance data in support of their causes. While the government statistics are aimed at informing opinion, the nonprofit statistics are aimed at influencing opinion. As we have shown, gullible journalists and researchers and the unsuspecting public cite the statistics produced by advocates in the same way that they cite those presented by government statistical agencies. If policy-makers allocate resources using the same flawed information, then they will target resources devoted to poverty relief incorrectly.

## References

- Abraham, K. G. (2003). Toward a cost-of-living index: progress and prospects. *Journal of Economic Perspectives*, 17(1):45–58.
- Adams, S. and Neumark, D. (2005). The effects of living wage laws: Evidence from failed and derailed living wage campaigns. *Journal of Urban Economics*, 58(2):177–202.
- Amior, M. and Manning, A. (2018). The persistence of local joblessness. *American Economic Review*, 108(7):1942–70.
- Auten, G. and Splinter, D. (2017). *Income Inequality in the United States: Using Tax Data to Measure Long-Term Trends*. Working Paper.
- Blank, R. M. (2008). How to improve poverty measurement in the United States. *Journal of Policy Analysis and Management*, 27(2):233–254.
- Brown, E. (2015). Building the living wage calculator. *MIT News*.
- Cavallo, A. and Rigobon, R. (2016). The billion prices project: Using online prices for measurement and research. *Journal of Economic Perspectives*, 30(2):151–78.
- Coleman-Jensen, A., Rabbitt, M. P., Gregory, C. A., and Singh, A. (2019). *Household Food Security in the United States in 2018*. US Department of Agriculture, Economic Research Service, Washington DC.
- DuMond, J. M., Hirsch, B. T., and Macpherson, D. A. (1999). Wage differentials across labor markets and workers: Does cost of living matter? *Economic inquiry*, 37(4):577–598.
- Ganning, J. P., Baylis, K., and Lee, B. (2013). Spread and backwash effects for nonmetropolitan communities in the US. *Journal of Regional Science*, 53(3):464–480.
- Gundersen, C. (2019). The right to food in the United States: The role of the Supplemental Nutrition Assistance Program (snap). *American Journal of Agricultural Economics*, 101(5):1328–1336.
- Gundersen, C., Dewey, A., Crumbaugh, A., Kato, M., and Engelhard, E. (2018). *Map the Meal Gap 2018: A*

- Report on County and Congressional District Food Insecurity and County Food Cost in the United States in 2016.* Feeding America, Chicago.
- Gundersen, C., Dewey, A., Hake, M., Engelhard, E., and Crumbaugh, A. S. (2017). Food insecurity across the rural-urban divide: Are counties in need being reached by charitable food assistance? *The Annals of the American Academy of Political and Social Science*, 672(1):217–237.
- Hausman, J. (2003). Sources of bias and solutions to bias in the consumer price index. *Journal of Economic Perspectives*, 17(1):23–44.
- Hotchkiss, M. and Phelan, J. (2017). *Uses of Census Bureau Data in Federal Funds Distribution: A New Design for the 21st century.* United States Census Bureau, Washington DC.
- Hughes-Cromwick, E. and Coronado, J. (2019). The value of US government data to US business decisions. *Journal of Economic Perspectives*, 33(1):131–46.
- Jarmin, R. S. (2019). Evolving measurement for an evolving economy: Thoughts on 21st century US economic statistics. *Journal of Economic Perspectives*, 33(1):165–84.
- Jolliffe, D. (2003). On the relative well-being of the nonmetropolitan poor: An examination of alternate definitions of poverty during the 1990s. *Southern Economic Journal*, pages 295–311.
- Kilkenny, M. (2010). Urban/regional economics and rural development. *Journal of Regional Science*, 50(1):449–470.
- Lewis Jr, W. and Johnson, C. (2018). Exploring changes in poverty in South Carolina during the great recession using a spatial Durbin model. *Journal of Regional Analysis & Policy*, 48(2):3841.
- Nadeau, C. A. (2018). *Living Wage Calculator User's Guide / Technical Notes.* <https://livingwage.mit.edu/resources/Living-Wage-User-Guide-and-Technical-Notes-2018.pdf>, Cambridge.
- Nadeau, C. A. and Glasmeier, A. K. (2019). New data up: Calculation of the living wage. <https://livingwage.mit.edu/articles/37-new-data-up-calculation-of-the-living-wage>.
- Partridge, M. D. and Rickman, D. S. (2008). Distance from urban agglomeration economies and rural poverty. *Journal of Regional Science*, 48(2):285–310.
- Partridge, M. D., Rickman, D. S., Olfert, M. R., and Tan, Y. (2015). When spatial equilibrium fails: Is place-based policy second best? *Regional Studies*, 49(8):1303–1325.
- Phillips, T. B. (2011). A living wage for research subjects. *The Journal of Law, Medicine & Ethics*, 39(2):243–253.
- Piketty, T., Saez, E., and Zucman, G. (2018). Distributional national accounts: Methods and estimates for the United States. *Quarterly Journal of Economics*, 133(2):553–609.
- Weber, B. A. (2007). Rural poverty: Why should states care and what can state policy do? *Journal of Regional Analysis & Policy*, 37(1):48–52.
- Werner, A. and Lim, M. (2016). The ethics of the living wage: A review and research agenda. *Journal of Business Ethics*, 137(3):433–447.
- Winters, J. V. et al. (2009). Wages and prices: Are workers fully compensated for cost of living differences? *Regional Science and Urban Economics*, 39(5):632–643.