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PRECISION IN ESTIMATES OF DISABILITY PREVALENCE FOR THE POPULATION AGED 65 AND OVER IN THE UNITED STATES BY RACE AND ETHNICITY

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Abstract

Background—Populations are aging worldwide. In the United States (US), the older adult (aged 65) population will increase rapidly in the decades to come. Identifying public health needs in older adults requires that sample-derived estimates of disability prevalence be produced using transparent methodologies.

Objectives—Produce estimates of disabilities for the US older adult population by race and ethnicity and present measures on the ‘level of precision’ in the estimates.

Design—Cross-sectional study used American Community Survey (ACS) Public Use Microdata Sample (PUMS) 3-year file collected during 2009-2011 survey period.

Setting—Community dwelling population aged 65 in US.

Participants—The 1,494,893 actual survey participants (unweighted count) are said to represent 40,496,512 individuals after population weights are applied (weighted count). From the weighted counts, the average age is 75, about 56% are females, and most (80%) are Non-Latino-Whites (NLW).

Results—Qualitative comparisons provide some evidence that except for hearing, disability prevalence is highest in Non-Latino-Blacks along the following disability items: independent living (25%); ambulatory (34%); self-care (15%); cognitive (11%); and vision (11%). Person inflation ratios, width of 95% confidence interval, and rates of allocations are smaller in NLWs than all the other race-ethnic groups—suggesting disability estimates for NLWs merit the highest level of confidence.

Conclusions—Improving measures of health in the older adult population requires that efforts continue to highlight how estimates of disability prevalence have the potential to vary in precision and as a function of various known and unknown factors.

Keywords

Self-care; ambulatory; independent living; vision; hearing; cognitive

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Introduction

Avoiding fatal diseases in late life frequently means encountering chronic illness instead (e.g., arthritis). Because gains in life expectancy need not be accompanied by a compression of comorbidity in late-life, the risk for experiencing some form of frailty before the onset of disability may be on the rise. As age increases, the individual may not necessarily become fully incapacitated but instead begin to become more limited in the ability to function independently (e.g., purchase groceries on their own). Reports show that nearly 40% of those over the age of 45 in the United States (US) report disability with physical movement (1), and that about 52% of the US population age 65 and over have some form of disability (2). According to recent estimates, the US population age 65 and over will increase to 88,546,973 by 2050—about 29 times the number from 1990 (3,080,498) (3). Disability in the older adult population has many social and economic implications for society as a whole.

Existing work has shown that disability varies as a function of socioeconomic status (SES)—where risk of reporting disability decreases as income increases (4). Research has frequently found that adverse health outcomes concentrate in race-ethnicity minority groups even after accounting for SES (5). In particular, concentration of risk for disability in older adult minorities has been shown to exist (6). Research on health disparities by race and/or ethnicity is influenced by the view that differences in health status are partially the product of unequal access to economic resources (7). If prevalence of disability in the population can be used as a surrogate measure for the prevalence of frailty in the population (as frailty is frequently considered a pre-disability condition), then understanding how frailty is distributed in the US population may help fulfill goals of the Public Health Service Act and Minority Health and Health Disparities Research and Education Act of 2000 aimed at findings ways of mitigating health differences between populations.

Understanding disability prevalence by race-ethnic groups in the population aged 65 and over may help public health professionals and policy makers understand the needs of the aging public. Because estimating disability rates is deemed important, publications have provided estimates of disability prevalence in the population (2, 6). It is important to note that publications have reported “population estimates” of disability by only using small samples (e.g., $n < 1,000$). Small samples are sometimes gathered by selectively choosing individuals from a sampling frame representing small geographical regions (e.g., < 400 square miles). Even when studies do make use of large-scale samples ($n > 50,000$) to estimate disability prevalence in the population, they fail to account for how uncertainty in the estimate varies between groups.

Uncertainty in estimates is present because in most (probably all) instances, a sample is used to infer characteristics about a population. Inferring characteristics of the population from information only available in the sample requires the use of statistical techniques. Extrapolating from a few (sample) to all (population) demands several statistical assumptions be met and even then, only a scientific approximation (i.e., estimate) on the characteristic of the population (i.e., “all”) can be derived from the sample (i.e., “few”). Consequently, when population estimates are discussed, it is implicitly known (at least

amongst experts) that the estimate represents the center-point in a set of symmetrically distributed group of plausible values.

Novice consumers of disability estimates may not fully appreciate implications from the idea that the mid-point estimate is only one of a set of plausible values bounded within some degree of statistical confidence (e.g., a 95% degree of certainty). When computing sample-derived estimates with frequentists statistical techniques (which prevail in public health research), the “true” population characteristic can be empirically estimated to within some range of confidence. These points are important as published work using sample data to discuss the prevalence of disability in the population frequently discusses the mid-point value without mentioning any measures on the precision of the estimate (e.g., 95% confidence intervals).

A hypothetical example may help. Assume a study reports 10% of the population has some form of disability. If the prevailing frequentists statistical approach is used, a more precise statement regarding this hypothetical 10% disability rate would be to state that authors are 95% confident the true estimate of disability in the population lies somewhere between two points (e.g., 8% and 12%). Note this is not a probability statement (i.e., “there is a 95% probability that”) and could more technically read: 95% of constructed intervals are expected to contain the true estimate if each interval is constructed from a different and random sample using the same measure of disability.

Figure 1 graphically represents a hypothetical scenario where the true disability rate in the population is 10%. Figure 1 is a visual representation of what is meant by “95% confident” from a frequentist’s point of view. The figure depicts how 19 out of 20 (95%) of the confidence intervals in a hypothetically scenario contain the true disability rate in the population. Note the distance between the center-points of the hypothetical confidence intervals and the true disability rate of a population differ. It is difficult to ascertain if the mid-point of a confidence interval, the most discuss estimate, more closely represents the true population estimate relative to any of the other values within the set of plausible values in the interval. The core argument with regards to confidence intervals is as follows: because population estimates only represent the mid-point of a confidence interval, they should be treated with great caution when attempting to understand between-group differences (e.g., health disparities).

The specific aim of this brief report is to present US population disability estimates by race-ethnic groups and show how confidence intervals around estimates vary by race/ethnic groups. The report helps inform literature by providing more transparent estimates of disability for the population aged 65 and over in the US.

Methods

Data

Estimates are produced by using Public Use Microdata Sample (PUMS) data files from the 3-year (from about January 2009 to December 2011) American Community Survey (ACS). The ACS is a population-based survey administered by the US Census Bureau. Data from

the ACS is very important as it helps the US government determine how to distribute hundreds of billions of dollars in federal and state funds (8). The ACS gathers responses on “difficulty” to perform the six tasks presented in Appendix A. Although the survey items could be improved, ACS provides high quality data for a very large number of older adults in the US population.

Sample

Individuals aged 65 and over make up the analytic sample. There are 1,494,893 unweighted subjects, which equal 40,496,512 weighted individuals. “Unweighted counts” reflect the actual number of subjects in the analytic sample, while the “weighted count” refers to the number said to be represented by the analytic sample after applying a single population weight. From the weighted counts, the sample has about 56% females and an average age of 75 (ranging from 65 to 95). The Person Inflation Ratio (PIR), the average number of people being represented in weighted population by the unweighted counts, is also presented and computed as follows: (weighted count ÷ weighted total population) (9). PIR roughly indicates severity of inference—where an increase in PIR is said to signal an increase in the quantity of inference.

Measuring Disability

There are six “disability” (label used by US Census Bureau) variables being used in the analysis. Appendix A lists the items and questions found in the ACS and used in analysis. Allocation flags for disability items are also used to determine number of “fixed” responses (10). Missing or illogical responses are allocated (i.e., assigned) a value through complex algorithms beyond the scope of the current study (10). The main point of showing the reader rates of allocation is to highlight how item-missingness (where the question is unit of importance) also varies by race/ethnicity. The production of confidence intervals around population estimates account for unit-missingness (where the person is the unit of importance). Not accounting for item-missingness (e.g., systemic item-response errors) may be shrinking the size of confidence intervals by failing to inflate the uncertainty produced through allocation algorithms.

Race and Ethnicity

Both race and ethnicity variables are used to create the following groups: Non-Latino-White (NLW); Non-Latino-Black (NLB); Non-Latino-Other (NLO); Mexican-Latino (MEX); and Non-Mexican-Latino (NML). Details on race and ethnicity are made widely available by the US Census Bureau online. The current coding scheme makes use of the most succinct race/ethnicity coding scheme—guided by group size.

Estimates and Standard Errors

By using 80 person-weights (PWGTP1-PWGTP80 variables) provided in the PUMS files, an algorithm (in SAS 9.3®) is created to compute error measurements (9). The “replicate weights method” produces standard errors (SE) by using the 80 “replicate weights” for each person (14). The estimates are used in the following formula:

$$SE(x) = \sqrt{\frac{4}{80} \sum_{r=1}^{80} (x_r - x)^2}$$

where x is the estimate based on PWGTP and x_r is the 80 individual estimates based on the replicated weights (11). The algorithm also computes the margin of error (MOE) and multiplies the computed SE by 1.96 to show 95% confidence intervals. The MOE symbolizes deviations between samples which may lead survey-based estimates to deviate from approximating the “true” population value. Deviations from the true count are estimated with standard errors (SE); where “upper” and “lower” 95% confidence limits around disability estimates are given. An easy to understand measure, Range of Uncertainty (RU), is calculated as follows: $[(SE*3) \div x]*100$, where x is the estimate. An increase in RU signals an increase in the level of imprecision (9). Noting esoteric challenges in quantifying estimates of disability prevalence is not an argument for the ‘high fallibility’ of ACS data. It is only because ACS data can be regarded as having high quality and transparency that microscopic limitations can be discussed in a public platform.

Allocations

Disability allocation “flag” variables (11) are used to estimate the weighed number of allocations and percent allocated as follows: $[(\text{weighted allocated count} \div \text{total weighted population}) * 100]$. Allocation refers to answers that are changed or assigned—i.e., original response, recorded by data entry protocol, is manipulated to produce a plausible response. Percent allocation is a proxy measure of data quality for a particular question and reminds readers that estimated confidence intervals do not account for the potential systematic errors (i.e., biases) caused by item-nonresponse patterns. These biases may in practice not be statistically unquantifiable (12). Please note that the discussion on uncertainty and potential influence of allocation rates on disability prevalence estimates is made possible by the fact that about 1.5 million real people are being used in an analysis that takes advantage of trustworthy ACS data. Size, quality, and transparency are rarely made available simultaneously.

Results

Table 1 shows the weighted and unweighted count of the analytic sample. It is clear that the majority (~80%) of the sample is made up of NLW subjects. NMLs make up the smallest unweighted count with 39,958 subjects. In general NLWs have a lower (PIR=26) inflation rate than all the other groups (e.g., NML PIR=33). Although a large number of comparisons can be made from the table provided in this report, only brief examples of how to interpret Tables 2 and 3 are provided below.

Table 2 shows what may be labeled as “lower extremity” disabilities. The estimates indicate that NLBs have the highest rates of disabilities for all items. For example, while NLWs have a 17.45% disability rate for “independent living,” NLBs have a 24.54%. Please note throughout the discussion that only “qualitative” comparisons between estimates are made because quantitative testing of statistically significant differences is not perform—as an

acceptable statistical technique that incorporates SEs and rates of allocation could not be found with frequentists statistical methods. Please note that NMLs have the largest (RU=7.60%) level of uncertainty in the independent living item and in general NLOs have the highest rate of allocations (e.g., self-care-NLO: %A=5.33%).

Table 3 shows what may be consider as “upper extremity” disabilities. In this table we see NLBs have the highest rate of “cognitive” and “vision” disabilities but not “hearing”—where NLWs have the highest rate at 16.42%. NMLs have the highest level of uncertainty around their estimate (RU≈11%) in the vision item. The cognitive item has the highest levels of allocations (from 3.14% to 5.40%) from all upper extremity disability items.

Discussion

Qualitative comparisons seem to indicate that NLBs have the highest rates of difficulty along the six ACS disability items. The highest levels of uncertainty in disability group estimates are found in NLOs, MEXs, and NMLs (the smaller sample groups). The greatest numbers of allocations for upper and lower extremity disabilities disabilities are generally found in NLOs. Future work should explore in greater detail why so many survey responses on disability items are being allocated in this population. These findings are important because frailty is frequently considered as pre-disability state (15). The empirical results suggest frailty may be most prevalent in socioeconomically marginalized populations in the USA. The brief report contributes to the literature on frailty and aging by providing race/ethnicity group disability estimates and measures of error around them for the US population age 65 and over. As the aging population continues to grow and given that disability has many social and economic implications, research should continue to explore how the quality of data varies for vulnerable populations and explore or suggest intervention strategies.

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Appendix A: “Disability” items from the American Community Survey

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- Independent living: Because of a physical, mental, or emotional condition, does this person have difficulty doing errands alone such as visiting a doctor’s office or shopping?
 - Ambulatory: Does this person have serious difficulty walking or climbing stairs?
 - Self-care: Does this person have difficulty dressing or bathing?
 - Cognitive: Because of a physical, mental, or emotional conditions, does this person have serious difficulty concentrating, remembering, or making decisions?
 - Hearing: Is this person deaf or does he/she have serious difficulty hearing?
 - Vision: Is this person blind or does he/she have serious difficulty seeing even when wearing glasses?
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References

1. Altman, B.; Bernstein, A. Disability and health in the United States, 2001–2005. National Center for Health Statistics; Hyattsville, MD: 2008.

2. Brault, M. Americans with disabilities: 2005. U.S. Census Bureau; Washington, DC: 2008. p. 1-24.
3. US Census Bureau. Projections for 2010 through 2050 are from: Table 12. Projections of the Population by Age and Sex for the United States: 2010 to 2050 (NP2008-T12), Population Division. US Administration on Aging. 2008
4. Minkler M, Fuller-Thomson E, Guralnik JM. Gradient of disability across the socioeconomic spectrum in the United States. *N Engl J Med*. 2006; 355(7):695–703. [PubMed: 16914705]
5. Braveman PA, Cubbin C, Egerter S, Williams DR, Pamuk E. Socioeconomic disparities in health in the United States: what the patterns tell us. *Am J Public Health*. 2010; 100(S1):S186–S196. [PubMed: 20147693]
6. Fuller-Thomson E, Nuru-Jeter A, Minkler M, Guralnik JM. Black-White disparities in disability among older Americans: further untangling the role of race and socioeconomic status. *J Aging Health*. 2009; 21(5):677–698. [PubMed: 19584411]
7. Mehta NK, Sudharsanan N, Elo IT. Race/Ethnicity and disability among older Americans. *Handbook of Minority Aging*. 2013:111–129.
8. Reamer, AD. Surveying for Dollars: The Role of the American Community Survey in the geographic distribution of federal funds. Metropolitan Policy Program at Brookings; Washington DC: 2010.
9. Siordia C, Le VD. Precision of Disability Estimates for Southeast Asians in American Community Survey 2008-2010 Microdata. *Central Asian J Global Health*. 2013 in press. DOI:10.5195/cajgh.2012.2166-7403.
10. Siordia C, Young RL. Methodological Note: Allocation of Disability Items in the American Community Survey. *Disability Health J*. 2013; 6(2):149–153.
11. Siordia C. Detecting “real” population changes with American Community Survey data: The implicit assumption of treating between-year differences as “trends”. *J Sociol Res*. 2014; 4(2): 494–509.
12. US Census Bureau. Design and Methodology American Community Survey. US Government Printing Office; Washington, DC: 2009.
13. Siordia C. Methodological Note: Allocations with Health Insurance Items in the American Community Survey. *J Frailty Aging*. 2013; 6(2):149–153.
14. US Census Bureau. A Compass for Understanding and Using American Community Survey Data: What PUMS Data Users Need to Know. US Government Printing Office; Washington, DC: 2009.
15. Baldwin MR, Reid MC, Westlake AA, et al. The Feasibility of Measuring Frailty to Predict Disability and Mortality in Older Medical-ICU Survivors. *J Crit Care*. 2014 in press. <http://dx.doi.org/10.1016/j.jcrc.2013.12.019>.

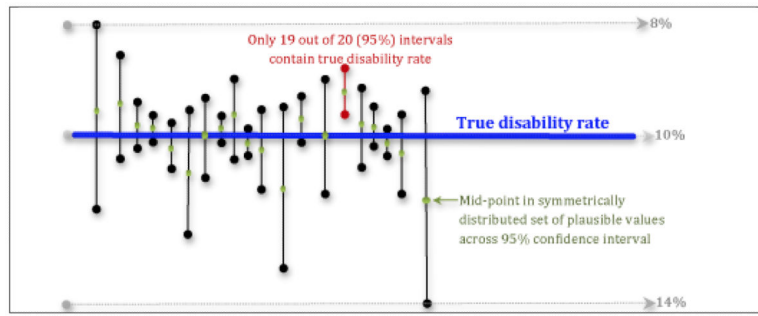


Figure 1.
Graphically, 95% of intervals contain the true estimate (e.g., 10%)

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Table 1Distribution of analytic sample (age ≥ 65) by race-ethnic group

	Percent [*]	Weighted Count [†]	Unweighted Count [‡]	PIR [§]
Non-Latino-White	79.89%	32,352,520	1,224,473	26
Non-Latino-Black	8.39%	3,398,932	116,385	29
Non-Latino-Other	4.78%	1,935,818	66,021	29
Mexican-Latino	3.66%	1,483,196	48,056	31
Non-Mexican-Latino	3.27%	1,326,046	39,958	33
Total	100%	40,496,512	1,494,893	27

* Percent within union-type= [weighted count \div total of weighted counts];

[†] Weighted number of people age ≥ 65 ;

[‡] Unweighted number of people age ≥ 65 ;

[§] Person Inflation Ratio: average number of people being represented in weighted population by the unweighted counts = (weighted count \div unweighted total population)

Table 2

Weighted disability estimates and measures of uncertainty for independent living, ambulatory, self-care items

Independent Living									
	Disable *	%D [†]	SE	MOE	LCL [‡]	UCL [§]	RU [#]	Allocated ^{**}	%A ^{††}
NLW	5,645,270	17.45%	14,323	28,073	5,617,197	5,673,343	0.76%	1,046,097	3.23%
NLB	834,067	24.54%	8,552	16,763	817,304	850,830	3.08%	182,540	5.37%
NLO	389,232	20.11%	7,891	15,467	373,765	404,699	6.08%	105,432	5.45%
MEX	338,439	22.82%	4,371	8,566	329,873	347,005	3.87%	67,194	4.53%
NML	283,859	21.41%	7,187	14,086	269,773	297,945	7.60%	68,434	5.16%
Ambulatory									
	Disable	%D	SE	MOE	LCL	UCL	RU	Allocated	%A
NLW	7,976,478	24.65%	27,591	54,079	7,922,399	8,030,557	1.04%	1,020,425	3.15%
NLB	1,168,781	34.39%	11,265	22,079	1,146,702	1,190,860	2.89%	172,830	5.08%
NLO	468,783	24.22%	4,776	9,360	459,423	478,143	3.06%	103,597	5.35%
MEX	454,511	30.64%	6,547	12,832	441,679	467,343	4.32%	64,035	4.32%
NML	370,298	27.92%	3,351	6,567	363,731	376,865	2.71%	66,251	5.00%
Self-care									
	Disable	%D	SE	MOE	LCL	UCL	RU	Allocated	%A
NLW	3,349,947	10.35%	20,320	39,827	3,310,120	3,389,774	1.82%	1,009,688	3.12%
NLB	515,031	15.15%	7,624	14,942	500,089	529,973	4.44%	172,759	5.08%
NLO	199,383	10.30%	4,072	7,982	191,401	207,365	6.13%	103,206	5.33%
MEX	206,737	13.94%	4,808	9,424	197,313	216,161	6.98%	63,615	4.29%
NML	165,858	12.51%	3,247	6,365	159,493	172,223	5.87%	66,274	5.00%

SE: Standard Error; MOE: Margin of Error; NLW: Non-Latino-White; NLB: Non-Latino-Black; NLO: Non-Latino-Other; MEX: Mexican-Latino; NML: Non-Mexican-Latino;

* Weighted number of people reporting difficulty with item;

[†] Percent disable (%D) = [(weighted disable count ÷ weighted total population) × 100] (Note: denominator available in Table 1);

[‡] 95% Lower Confidence Limit (LCL) = [Disable – MOE];

[§] 95% Upper Confidence Limit (UCL) = [Disable + MOE];

[#] Range of Uncertainty (RU) = {[SE × 3] ÷ disable} × 100};

^{**} Number of responses to disability item which are assigned or changed (includes non-disable individuals);

^{††} Percent Allocated (%A) = [(weighted allocated count ÷ weighted total population) × 100] (Note: denominator available in Table 1)

Table 3

Weighted disability estimates and measures of uncertainty for cognitive, hearing, and vision items

Cognitive									
	Disable *	%D[†]	SE	MOE	LCL[‡]	UCL[§]	RU[#]	Allocated^{**}	%A^{††}
NLW	3,340,452	10.33%	13,113	25,702	3,314,750	3,366,154	1.18%	1,014,836	3.14%
NLB	528,005	15.53%	5,608	10,991	517,014	538,996	3.19%	175,503	5.16%
NLO	231,252	11.95%	4,036	7,911	223,341	239,163	5.24%	104,579	5.40%
MEX	211,920	14.29%	2,788	5,464	206,456	217,384	3.95%	63,830	4.30%
NML	194,226	14.65%	5,974	11,709	182,517	205,935	9.23%	66,721	5.03%
Hearing									
	Disable	%D	SE	MOE	LCL	UCL	RU	Allocated	%A
NLW	5,310,752	16.42%	18,008	35,297	5,275,455	5,346,049	1.02%	859,033	2.66%
NLB	365,961	10.77%	4,443	8,709	357,252	374,670	3.64%	145,539	4.28%
NLO	262,556	13.56%	3,090	6,056	256,500	268,612	3.53%	77,490	4.00%
MEX	247,618	16.69%	5,015	9,829	237,789	257,447	6.08%	52,240	3.52%
NML	162,986	12.29%	2,566	5,029	157,957	168,015	4.72%	55,997	4.22%
Vision									
	Disable	%D	SE	MOE	LCL	UCL	RU	Allocated	%A
NLW	2,217,473	6.85%	18,949	37,140	2,180,333	2,254,613	2.56%	1,115,682	3.45%
NLB	362,861	10.68%	4,929	9,661	353,200	372,522	4.08%	166,883	4.91%
NLO	140,940	7.28%	3,462	6,786	134,154	147,726	7.37%	85,241	4.40%
MEX	162,348	10.95%	2,600	5,095	157,253	167,443	4.80%	58,445	3.94%
NML	128,275	9.67%	4,707	9,225	119,050	137,500	11.01%	59,871	4.52%

SE: Standard Error; MOE: Margin of Error; NLW: Non-Latino-White; NLB: Non-Latino-Black; NLO: Non-Latino-Other; MEX: Mexican-Latino; NML: Non-Mexican-Latino;

* Weighted number of people reporting difficulty with item;

[†] Percent disable (%D) = [(weighted disable count ÷ weighted total population) × 100] (Note: denominator available in Table 1);

[‡] 95% Lower Confidence Limit (LCL) = [Disable – MOE];

[§] 95% Upper Confidence Limit (UCL) = [Disable + MOE];

[#] Range of Uncertainty (RU) = {[SE × 3] ÷ disable} × 100;

^{**} Number of responses to disability item which are assigned or changed (includes non-disable individuals);

^{††} Percent Allocated (%A) = [(weighted allocated count ÷ weighted total population) × 100] (Note: denominator available in Table 1)