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Disability Estimates between Same- and Different-Sex Couples: Microdata from the American Community Survey (2009–2011)

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Abstract

Disability and sexual orientation have been used by some to unjustly discriminate against differently-abled and differently-oriented minority groups. Because little is known about the disability rates of individuals in same-sex unions, this technical report presents disability rates by separating couples into: same-sex-female; same-sex-male; different-sex-married; and different-sex-unmarried couples. Data from the American Community Survey (ACS) Public Use Microdata Sample (PUMS) 2009–2011 3-year file is utilized to produce estimates (and their standard errors) for the following six disability items: independent living; ambulatory; self-care; cognitive; hearing; and vision. Estimates of disability by selected geographies—i.e., Public Use Microdata Areas (PUMAs)—are also presented as is a figure showing a PUMA polygon. Qualitative comparisons seem to indicate that: same-sex-female couples have higher rates of disability compared to the other three groups; that in general, disability estimates for individuals in same-sex couples have a greater degree of uncertainty; and that disability-item-allocations are most prevalent in same-sex couples. Because societal marginalization may increase through cumulative processes, public health professionals should continue to seek out ways to identify underserved populations.

Keywords

Same-sex; Disability; United States; ACS; PUMS; PUMA; DOMA

Introduction

About fifty million people in the United States (US) live with some form of disability [1]. Having a long- or short-term physiological condition which prohibits an individual from navigating the able-body-customized social and physical environments unjustly burdens the differently-able person. Because differently-able [2] individuals must confront multifaceted disadvantages, public health policy should continue efforts to mitigate inequalities between able-body and people or individuals with disabilities (or a disability). Disadvantages may operate in an additive function to impair the social success and physical health of

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individuals. Exploring disabilities by socially stratifying characteristics (e.g., sexual orientation), may allow public health researchers the ability to explore the degree to which cumulative disadvantage is concentrated along unjustly marginalized groups [3]. If we assume being physically disabled is a disadvantage-causing condition that can be compounded upon by other socially stratifying characteristics (e.g., race), and that individuals in same-sex unions have an above average risk of being socially marginalized [4], then we should consider how disabilities vary between same- and different-sex couples. Publish work has given some evidence that the well-being of members of stigmatized groups is influenced by how they interact with their devalued collective identity [5] and that individuals from same-sex couples experience discrimination [6]. In this paper, it is assumed same-sex couples have an above average likelihood of having to face unique social and economic challenges—relative to different-sex couples. The assumption is based on evidence [7]. The investigation adds to existing literature by providing the most reliable and valid prevalence estimates for six disability factors by couple-type.

For millennia, world travelers had visited the geographical region currently referred to as the United States (US). Native dwellers in the areas witnessed European colonization during the 16th century. By 1776, the colonizers declared independence from the government in their homeland (i.e., Great Britain). The Caucasian-US was established through immigration motivated by ideologies framed in Judeo-Christian world views—were heterosexual marriages between Caucasians were the only unions worthy of procreating to populate the new world. Since then, the US has slowly morphed towards a more secular society. However, discrimination by economic status, skin color, sexual orientation, religious affiliation, language, and many other factors remains common. Under the view that an individual’s health is a product of her/his biological constitution and the environment, the project shows how prevalence of disability varies by couple-type.

Although living arrangements in the US continue to change and current reports indicate that there are more than a half-million same-sex couple households in the US [8], same-sex couples continue to experience discrimination as both laws and social norms prohibit them from obtaining complete social acceptance. If laws and popular public opinion (as depicted by media outlets) have the potential to negatively affect individuals in “untraditional” relationships (e.g., unmarried partners and same-sex couples) [9], then investigating if disability rates differ by couple-type is important for public health as evidence does exist that social networks are correlated with various health outcomes. For example, research has shown stable relationships help develop and maintain good health [10]. Same-sex couples may benefit differently (less so) from their stable relationships than different-sex couples if they experience social marginalization. Indeed, research using data from the 1997 to 2009 National Health Interview Surveys on 1,659 same-sex-male couples and 1,634 same-sex-female couples found same-sex couples report poorer health than their different-sex-married counterparts [10]—a difference presumed to be partially produced from their same-sex couple status. This technical report makes use of data gathered by the US Census Bureau, the official federal government agency charge with gathering information on the US population, to produce estimates of disability prevalence by couple-type.

The term “couple” is used as a blanket label to refer to “married” and “unmarried” partnerships. The use of the generic term couple is partially necessary because of the non-theory driven information editing protocols utilized in the data being used in the analysis. In this paper, couple refers to dichotomous partnerships where a ‘notable commitment to the relationship’ is assumed to have been reported between same- or different-sex partnerships. From this view, it is presumed that individuals who report to be related to another as “husband/wife” or “unmarried partner” are both equally characterizing a serious, non-platonic, and primarily monogamous relationship. “Primarily monogamous” because there is evidence that mammalian species have the potential for having multiple mates at one time [11, 12]. Couples are treated as dyads in a system where males imposed and/or females self-impose monandry (i.e., female has one *husband* at a time) and where females impose and/or males self-impose monogyny (i.e., male has one *wife* at a time). Because monandry and monogyny are typically understood and used to describe different-sex couples, the terms *andro-monandry* and *gyne-monogyny* are introduced. Andro-monandry refers to male-on-male imposed and/or self-imposed monandry. Gyne-monogyny refers to female-on-female imposed and/or self-imposed monogyny. These terms may help re-shift the heteronormativity-centered discourse on human relationships [13].

In the US, both federal and state governments have differed in how they recognized relationships over the last decades [14]. A crucial point to be made here is that the US Census Bureau is legally obligated to flag same-sex spouses as “invalid” in order to legally comply with the 1996 Federal Defense of Marriage Act (House of Representatives Bill #3396)—commonly referred to as DOMA (i.e., Defense of Marriage Act) [15]. Political decisions, by non-US Census Bureau data editing statisticians, have created laws that demand survey statisticians at the US Census Bureau “edit” data according to some politically motivated point of view. Data edits can refer to changing or assigning responses for survey items. Changes to responses may occur when for example responses do not fit the “logic” outline by the law or when the survey participant does not offer a response to the question. In either case, data is being manipulated in such a way as to merit attention.

Because of DOMA, data editing protocols at the US Census Bureau change “husband/ wife” responses by same-sex couples to “unmarried partner” [16]. This means husband/ wife responses by couples of the same-sex get changed to unmarried partners [17]. DOMA legally forces data editing protocols at the US Census Bureau to treat “spouse” as a status that can *only* exist in different-sex couples [18]. By extension, DOMA demands that US Census Bureau survey statisticians change husband/wife responses in same-sex couples to unmarried. Readers should note treatment of data may reflect the views of contemporarily influential politicians—whose opinions are assume by some to be an accurate reflection of the attitudes in the constituents they purport to represent. Data editing protocols denying same-sex couples the ability to claim the “married” label may be seen by some as an effort to marginalize the social legitimacy of same-sex unions. Beyond the legalese, relationship labels may play an important role in symbol informed societies [19]. DOMA forced data editing protocols that change married-same-sex couples to “unmarried” could be argued to unjustly rob these couples of their ability (i.e., agency) to self-define and label one of the most important relationships in the life course of any human. This matters because research has shown that as far as health benefits are concerned"cohabitating" relationships in the US seem to have fewer benefits from their union than married individuals [20]. Although semantic in nature, the politically driven data editing protocols used at the US Census Bureau—at the behest of existing laws—may be unintentionally affecting the health of same-sex couples in the US. This may explain why in recent times, the framing of inequality for same-sex couples has used language in the US Constitution to advocate for their civil rights in an effort to socially legitimatize their relationships [21].

Changing survey responses by same-sex couples may seem logical to some and controversial to others. From the view of a "data scientist"—a person interested in the processes used to collect, edit, and disseminate information on human phenomena—it is intriguing to observe how non-empirically driven forces (e.g., decision by politicians) influence the reliability and validity of data. This fact seems to be at times ignored when quantitative data is utilized in complex statistical procedures that aim at validating numbers as reflecting some absolute and truthful measure of human phenomena.

The US Census Bureau is transparent about their editing procedures for same-sex survey responders. By using their internal non-edited data, they have shown that about one-fourth of all same-sex couple households in 2010 reported their status as "married" [8]. Regression analysis with their non-edited internal data also shows that same-sex couples are more likely to report as "husband or wife" if they are raising children and reside in states where same-sex marriage is legal [22]. Public data users are only allowed access to "internal" data files under very control conditions and through a selected number of access point (e.g., Research Data Centers). What should be made clear here is that the US Census Bureau does not have the power to make legal decisions—because the procedures by which they manage data is mandated by laws being created by individuals outside the US Census Bureau. If changing the responses of same-sex couples who report being "married" to "unmarried" seems peculiar, you should note that in previous years (e.g., 1990 and 2000), US Census Bureau editing procedures were required by law to change the sex of one person in a same-sex couple when they reported being married or unmarried partners [23]. In other words, data editing algorithms would change the "sex" (from male to female or vice versa) of one of the individuals detected to be in a same-sex union. Currently "sex" is no longer edited in data cleaning protocols, instead, same-sex unions reporting a husband/ wife status are changed to an unmarried partner status. Data editing procedures at the US Census Bureau are born out of laws created by political agents external to the agency. If the goal is to alter data editing protocols to improve the precision of publicly available data, then efforts should be focused on the source of influece, i.e., politicians—not an easy target to influence without lobbyist [24, 25].

Although previous work has shown some demographic estimates of the lesbian and gay population [26], no existing publication shows disability rates between same-sex-female, same-sex-male, different-sex-married, and different-sex-unmarried couples. The specific aim of this technical communication is to provide non-expert readers, interested in the topic of health in same-sex unions, with disability estimates by couple-type. In addition, disability estimates for same-sex couples are presented for a selected number of geographies where their population is most concentrated. The discussion of the disability prevalence by couple-type is complemented throughout by highlighting how different data management procedures have the ability to influence confidence in the statistical products created from sample data.

Methods

Data

Two approaches can be used to describe the characteristics of a population: survey everyone in the population (i.e., conduct a census); or survey a "sample" from the population. The first approach is very expensive and impractical, while the second produces information typically relegated for the digestion of expertly trained technicians. A sample is a group of individuals selected from the target population. Their selection into the study requires sophisticated procedures in order to insure that everyone in the target population is given an equal change of selection—a necessary property for using statistical procedures. According to probability and normal distribution theories from statistics, randomly chosen samples can be used to infer the characteristics of the population from which they were drawn. In different words, information from the sample can be used, within a certain degree of confidence, to "generalize" to the target population.

This study makes use of detailed information from a sample of 4,086,732 individuals residing in the US between 2009 and 2011. These American Community Survey (ACS) participants were abstracted from Public Use Microdata Sample (PUMS) files. The ACS collects information on more than 3 million people each year. This study uses information collected over a 3-year period: 2009–2011. Data from the ACS is very important as it helps the US federal government determine how to distribute hundreds of billions of dollars in federal and state funds. For example, in fiscal year 2008, 184 federal domestic assistance programs used information gathered by the ACS to influence the distribution of $416 billion (29 %) of all federal assistance and about $389 billion (69 %) of all federal grants funding [27]. The 3-year ACS PUMS file used in the analysis represents information collected on the US population over a 36-month period (from about January 2009 to December 2011). The US Census Bureau uses these data to produce estimates for geographies with as little as 20,000 people. Although the ACS PUMS data has limited health related survey items, it is the most detailed and large publicly available information on the US population. Despite limited information on health status in ACS data, its large sample and transparent data quality measures stand in stark contrast to prevailing norms that make use of a few hundred non-randomly collected people, concentrated over a small geographical area, to infer the characteristics of the US population. The disability estimates in this analysis are amongst the most (if not the most) generalizable to the US population.

Sample

The analytic sample (i.e., universe or origin of numbers in the denominator used in calculations) is made up of all individuals in a married or unmarried partnership. Couples of any age are identified with the following categories: same-sex-female (SSF) couples; same-sex-male (SSM) couples; different-sex married (DSM) couples; and different-sex unmarried (DSU) couple. The estimates being presented in the tables use a total of 4,086,732 unweighted subjects (i.e., real count of people participating in the survey and referred hereafter too simply as the "unweighted sample"). A single person-weight is used to compute "weighed" versus "unweighted" estimates. When these individual respondents are "weighted up"—using population controls to represent the US population and with a single variable (PWGTP)—the unweighted analytic sample is said to represent a count of 125,643,844 (here after only referred to as "weighted sample"). Population weights are partially influenced by using the probability of selection into the study [28] and are necessary for generalizing the findings from a sample to the target population (i.e., the US). In less technical terms, personal information from the 4,086,732 is used to describe the characteristics of the 125,643,844 individuals they are said to represent. Data products by the US federal government only make use of weighted estimates. In this report, weighted estimates are used to calculate disability prevalence and unweighted counts are continually shown to remind the reader the information is being derived from a sample of the population.

DOMA Editing Protocol

Because House of Representatives Bill 3394 (H.R.3394) dictates that all federal agencies only allow different-sex couples to self-identify as "married," data editing programs at the US Census Bureau are legally mandated to invalidate same-sex husband/wife responses and changes them to "unmarried" partnerships. The PUMS data files use "allocation flag" variables to identify instances when the originally entered response is changed. Allocation refers to the act of assigning a new value to a response. The term flag signals when the value of a variable has been allocated. Even though a marital status allocation flag (i.e., variable that allows public data users to identify when a variable has undergone a change because of an editing procedure) is available inACS2009-2011 PUMS files, the flag variable does not allow public data users to detect if a change on the marital status responses occurred because of an invalid (i.e., missing value) or unallowable (same-sex couple identifying as married) original value. Rates of allocation are shown in the tables to give readers an insight on how the level of occurrence varies by the various demographic factors under examination. The main point here is that as the rate of allocation increases, it is possible that more same-sex couples are being denied the right to self-identified as married.

Disability

There are six "disability" (label used by US Census Bureau) variables being used in the analysis, the item label is followed by the survey question:

1. Independent living
    a. 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?
2. Ambulatory
    a. Does this person have serious difficulty walking or climbing stairs?
3. Self-care
    a. Does this person have difficulty dressing or bathing?

4. Cognitive

   a. Because of a physical, mental, or emotional conditions, does this person have serious difficulty concentrating, remembering, or making decisions?

5. Hearing

   a. Is this person deaf or does he/she have serious difficulty hearing?

6. Vision

   a. Is this person blind or does he/she have serious difficulty seeing even when wearing glasses? [29].

The assessment of disablement is complex and continues to evolve. There are no gold standards for which factors should be assessed and how they should be measured. The first three items (i.e., independent living, ambulatory, and self-care) are associated with the frequently measure activities of daily living. The last three items (i.e., cognitive, hearing, and vision) could be argued to be more related with physical status than with the selfreported physical function. Responses to these questions may also be affected by more than their wording (e.g., placement in the survey instrument, language of survey, etc.). The main point with any of these items is that the survey participant responding to the questions identifies an individual as having some form of difficulty with the various tasks.

Statistical Approach

When information from a sample is used to infer the characteristics of the target population, it is important to note the concept of a "point estimate" and its "confidence intervals" [30]. A point estimate typically refers to the mid-point between two confidence intervals and the latter to the fact that inferring population characteristics from a sample requires the use probability theory from statistics. By using a series of mostly testable statistical assumptions, a sample can be used to scientifically guess the "true" population characteristic to within a 90, 95, or 99 %confidence level. For example, amongst same-sex female couples there are 25,450 who experience independent living difficulty (see Table 2). However, we can only be 90 %certain that the true population characteristic lies somewhere between 26,660 and 30,420. In theory, 90 times out of 100, one of the values between 26,660 and 30,420 would be produce if we measured the variable and selected the sample in exactly the same way. A greater degree of confidence (e.g., 99 %) would expand the range of probable numbers representing the true population characteristic. Note confidence on the degree of precision includes all the values within the 90 % confidence interval—the mid-point is not superior to any other value in the confidence interval (i.e., 24,450 is not more precise than any other number from 26,660 through 30,420). A point estimate is only one of many plausible values on which the true population characteristic may lie. The probability that a number within the range represents the true population value is equal for all the numbers in the confidence interval—that is, the mid-point is just the center of a symmetrical confidence interval and should be treated as one of many plausible values.

Complex calculations with multiple weights are required to estimate the confidence intervals for the point estimates being presented in the report. The US Census Bureau's transparency allows public data users to utilize 80 person-weights (PWGTP1-PWGTP80 variables) from the PUMS files to compute necessary estimates. An algorithm was developed using SAS 9.3® statistical software and the 80 person-weights by following publicly available instructions [30, 31]. The “replicate weights method” produces standard errors (SE: standard deviations from the sampling distribution) by using the 80 replicate weights for each person record and producing the estimate 80 times. The PWGT computed estimate and the 80 estimates from the replicate weights are then used in the following formula:

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

where x is the estimate based on PWGTP and x_r is the 80 individual estimates based on the replicated weights. The algorithm used in the analysis computes the margin of error (MOE) for each point estimate to highlight the uncertainty around the estimates—i.e., the range of plausible values. The algorithm multiplies the computed SE by 1.645 to show the MOE value needed to produce 90 % confidence intervals. The algorithm could be made to estimate 95 or 99 % confidence intervals by multiplying SE by 1.96 or 2.575 respectively. The project abstains from producing 95 and 99 % estimates because some the small unweighted sample sizes may not warrant such a level of precision [32]. The MOE symbolizes variation between samples—a deviation which may lead survey-based point estimates to deviate from approximating the true population value. Deviations from the true population value are mostly captured by 90 % confidence intervals and estimated via MOEs [33]. Less technically, SEs and MOEs are used to calculate confidence intervals and show within what range of numbers we can be about 90 % confident that the true population estimate exists.

Range of Uncertainty (RU), a potentially more easy to understand measure, is also used and calculated as follows: [(SE*3) ÷ x]*100, where x is the estimate. An increase in RU signals an increase in the level of imprecision—i.e., a larger set of plausible values [33]. While SEs and MOEs measure imprecision related with random process (i.e., unsystematic errors), there are other non-random mechanism (e.g., flawed question) that could affect the reliability and validity of the confidence intervals. The Person Inflation Ratio (PIR), the average number of people being represented in weighted population by the unweighted counts, is presented in order to provide readers with a proxy measure of much measurement bias could be propagating to infect the estimation of confidence interval. For example, a person with a PIR of 25 represents 25 other individuals with similar attributes, while a person with a PIR of 50 is allowed to represent 50 of his/her counterparts. More simply, as PIR increases, an individual represents more of his/her counterparts—thus, if a bias is introduced by said individual, its effect on the stability of confidence interval will magnify as a function of how many individuals that person is said to represent. PIR is computed as follows: (weighted count7weighted total population). PIR provides a proxy measure on the degree to which the sample is being used to generalize to the population—larger PIR numbers signal that a much larger inference about the group is being made from the sample.

The allocation “flag” variable in PUMS files [34] is used to estimate the weighed number of allocations and percent allocated in disability items by couple-type. Percent allocated is calculated as follows: [(weighted allocated count ÷ total weighted population)* 100]. These measures are presented to introduce non-experts to the fact that point estimates and their confidence intervals also have error structures which may bias them away from true population values through systematic errors (i.e., biases) in the data— measurement errors which may not be statistically quantifiable [35]. Throughout the discussion, only "qualitative" comparisons between estimates are made as no known statistical technique allows for the inclusion of all plausible values within a confidence interval in trying to ascertain if a statistically significant difference exist between the two groups.

Qualitative comparisons consist of using simple arithmetic to compare between two groups. For example, by observing (see Table 2) that same-sex females have a higher (7.53 %) rate of ambulatory difficulties than different-sex unmarried couples (4.73 %), we can conclude that ambulatory disability seems more prevalent amongst the first group of couples. The term "qualitative comparison" is used as inferential statistics are not utilized to determine whether differences are statistically significant. Determining the statistical significance of an event through frequentist approaches requires that the user assume stochastic processes govern human phenomena (i.e., the philosophical assumption that even if the initial condition is known, there are several directions in which a process may evolve). The qualitative comparison approach being used here is partially motivated by the epistemological view that the *social significance* of observed health differences between groups of people can be validated by showing persistent trends over a wide range of data sources, time periods, and geographical locations. More pragmatically, statistical significance may not help inform policy as much as making use of large high quality data sources capable of producing transparent and understandable estimates.

Geography

Previous work has shown couple-types vary by geography [36, 37]. In order to provide a geographical component to the analysis, the top-30 Public Use Microdata Areas (PUMAs) with the highest concentration of same-sex couples are identified. PUMA geographies are built by using "blocks" and are only delineated to facilitated administrative needs. These top-30 PUMAs represent about 1.45 % of all 2,070 PUMAs in the analytic sample. In addition to the table with the top-30 PUMAs with the most concentration of same-sex couples, a figure showing a PUMA—as it is not an easily definable geographical entity—is provided. The main point is making use of PUMAs is to show readers that the data can be geographically referenced and that studies could be conducted to investigate if disability prevalence varies by geography within same–same couple types.

Results

Table 1 shows the weighted and unweighted count of the analytic sample by couple-type. As can be seen from the table, 89.3 % of all couples are in different-sex-married (and presumed) monandry and monogyny relationships. In total, about 1 % of the US population is in a same-sex (and presumed) andro-monandry and gyne-monogyny relationships. The data does not allow us to identify or quantify the presence of individuals with multiple partners, hence the important reminder that in the paper, couples are seen as only have one partner each. From Table 1, we also see that on average different-sex unmarried couples represent more of their counterparts after being weighted up (i.e., PIR = 36.6). This means that individuals from different-sex unmarried couples on average represent more of their different-sex unmarried couples than individuals from other couple types.

Table 2 shows disability items which may be associated with commonly measured activities of daily living. The tables provide the ability for readers to make rich comparisons. Here, only a few items are highlighted. In Table 2, same-sex female couples have the highest rate of “independent living” disability (4.61 %) and in general, same-sex couples have higher level of uncertainty (SSF = 12.02 %; SSM = 19.17 %) in their estimates and higher rates of allocations (3.08 %) when qualitatively compared to DSM and DSU couples. In general, disability is most prevalent in females. We also see that SSF (7.53 %) and DSM (6.55 %) have the highest levels of “ambulatory” difficulties. SSM have the highest range on uncertainty in the ambulatory item (12.53 %). It should also be noted that individuals in DSU may be on average younger in age than the other groups. From the “self-care” difficulty, we see SSF (2.63 %) report the highest level of disability. Here too both SSF and SSM have the highest RU (SSF = 13.45 %; SSM = 20.41 %) and rates of allocation (SSF = 2.89 %; SSM = 2.81 %). Although the higher rates of uncertainty for both SSF and SSM couples may be partially a function of their small populations, the allocation rate is presumed to function independent of population size.

Table 3 shows what may be consider as “upper extremity” disabilities. SSM couples have the highest level of “cognitive” difficulty (4.36 %), while DSM have the heist level of “hearing” difficulties (4.20 %), and DSM of difficulties with “vision” (2.02 %). To guide the reader on how to interpret confidence limits, an example is made. From Table 2, we see there are an estimated 20,403 of individuals in SSM unions with a cognitive difficulty. We are 90 % that the true estimate is found somewhere between 18,916 and 21,890. To help highlight the interpretability of allocation rates an example is also given. From Table 2, SSF have 2.31 % of their hearing difficulty responses allocated (i.e., changed or assigned) compared to DSM with a 1.78 % allocation rate. This means that in a group of 1,000 people, SSF would have about 23 with an allocation while DSM would only have about 17 with an allocation on the hearing difficulty item. As with Tables 1, 2 also shows same-sex couples have larger ranges of uncertainty about their estimates and a higher rate of disability item allocation.

Table 4 shows the top-30 PUMAs with the highest concentration of same-sex couples. The disability estimates show the number with a disability amongst same-sex couples only. In PUMA number “602204”—located somewhere in San Francisco County, California—17.7 % of all couples are of the same-sex. This PUMA has about 2.0 % of individuals in a same-sex relationship reporting a difficulty with independent living, 1.8 % with an ambulatory difficulty, 0.5 % with a self-care difficulty, 2.3 % with a cognitive difficulty, 1.3 % with a hearing difficulty, and 0.9 % with a vision problem. This most same-sex couple concentrated PUMA is followed by another in the District of Columbia, and a PUMA in New York County, NY and Fulton County, GA. These 30 PUMAs represent the only geographies where same-sex couples make up 5 % or more of the couples population. Miami-Date County, FL seems to have the highest rate of disability amongst same-sex couples relative to all the other top-30 PUMAs. In contrast, individuals in same-sex unions who reside in a PUMA (# 2400805) in Baltimore City, MD report no difficulties with anything.

Because PUMAs are so heavily discussed, Fig. 1 displays PUMA number 5301805, which is one of the top-30 PUMAs located in Table 4. On the top-left of the figure, the Washington state geographical boundary is given followed by the county boundaries within the state. At the bottom-left, the King County geographical boundaries are presented (extracted from the county map in the center-left) with PUMA #5301805 highlighted in green within the county. To the right in Fig. 1, the geography of PUMA #5301805 is shown along with bodies of water in the area and some major roads. As can be visually appreciated, the geometrical anatomy of PUMA geographies is complex [38].

Conclusions

There are some limitations with the study. Primarily, the statistical significance of different rates is not discussed. For those interested in measuring health disparities, this may be a serious limitation. An adequate statistical test would have to consider that all the values within the confidence intervals are as plausible as the mid-point-estimate. Although the use of common procedures (e.g., *t* test on mean difference) would be an acceptable approach by current standards, it is avoided as the main objective of the project was to show the prevalence of disability by couple type and in doing so highlight the various eccentricities involved in the estimation process. At times, it may be necessary and helpful to produce high quality population estimates without having to determine statistical significance.

Future work should also be undertaken to explore how disability rates amongst samesex couples vary as a function of educational attainment [10]. Because previous work shows ACS 2010 data reports 593,000 same-sex households while data from the decennial in the same year estimated 902,000 same-sex households—an over-reporting difference believed to have been caused by the misreporting of sex [39], research should be undertaken to determine the misreporting of sex in the ACS. For example, the current project does not explore “sex allocation flags” in the data. Future work could replicate the current study and exclude individuals who had their sex response changed during data editing protocols. On a more precarious note, investigators should begin a public discussion on whether the investigation undertaken in this project has the potential to become dual use research—where the intention to benefit potentially disenfranchised individuals is misapplied by others in order to create harm. In particular, because PUMAs are driven by population density (i.e., highly dense areas contain geographically small PUMAs), the research community may want to consider if a minimum size threshold for publishable PUMAs should be established.

In summary, it is found that only about a 1 % of the US population is in a same-sex union. In general, females in same-sex couples seem to have the highest rates of difficulty along the six ACS disability items—this may be partially influenced by the fact that disability prevalence is highest amongst females. In all instances, individuals in same-sex couples have higher rates of allocation and their disability estimates have a higher rate of uncertainty. Notwithstanding the limitations, the current paper offers what may be a resource rich set of tables providing estimates of disability by couple-type. Public health research should continue to identify populations at risk for disability and explore or suggest intervention strategies.

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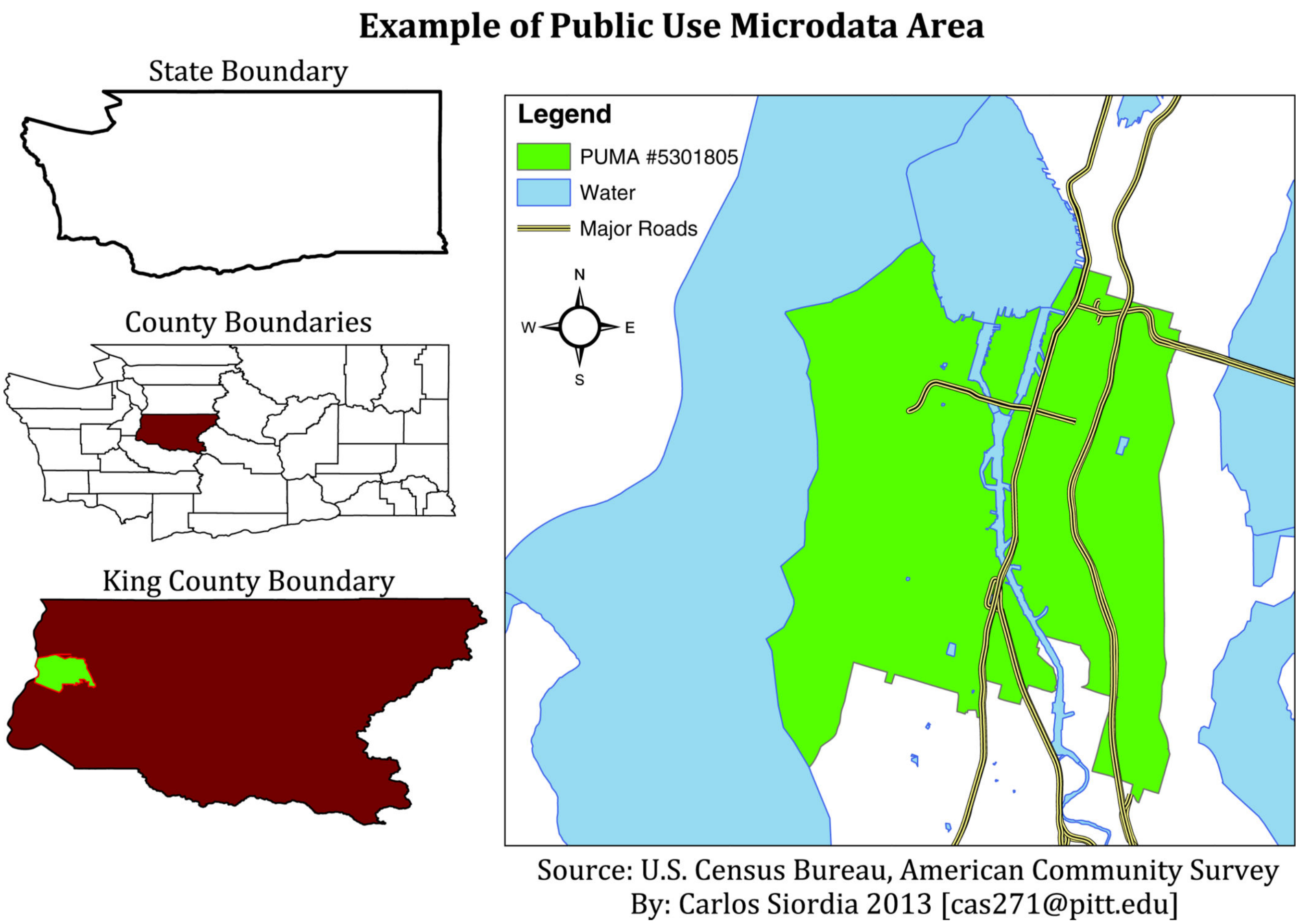

Fig. 1.
Example of public use microdata area

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Table 1

Analytic sample distribution by union-type

	Percent[a] **(%)**	**Weighted count**[b]	**Unweighted count**[c]	**PIR**[d]
Same-sex-female	0.5	619,023	20,738	29.8
Same-sex-male	0.5	567,577	18,990	29.9
Different-sex-married	89.3	112,223,539	3,713,098	30.2
Different-sex-unmarried	9.7	12,233,705	333,906	36.6
Total	100	125,643,844	4,086,732	30.7

[a]Percent within union-type = (weighted count 7 total of weighted counts)

[b]Weighted number of people

[c]Unweighted number of people

[d]Person inflation ratio (PIR): average number of people being represented in weighted population by the unweighted counts = (weighted count ÷ weighted total population)

Table 2

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

	Disable[a]	%D[b]	SE[c]	MOE[d]	LCL[e]	UCL[f]	RU[g] (%)	Allocated[h]	%A[i]
Independent living									
Same-sex female	28,540	4.61	1,143	1,880	26,660	30,420	12.02	19,035	3.08
Same-sex male	20,436	3.60	1,306	2,148	18,288	22,584	19.17	17,479	3.08
Different-sex married	4,045,347	3.60	14,569	23,966	4,021,381	4,069,313	1.08	2,476,943	2.21
Different-sex unmarried	329,433	2.69	6,267	10,309	319,124	339,742	5.71	263,017	2.15
Ambulatory									
Same-sex female	46,629	7.53	1,363	2,242	44,387	48,871	8.77	17,976	2.90
Same-sex male	27,543	4.85	1,150	1,892	25,651	29,435	12.53	16,149	2.85
Different-sex married	7,351,914	6.55	26,571	43,709	7,308,205	7,395,623	1.08	2,457,039	2.19
Different-sex unmarried	578,718	4.73	10,138	16,677	562,041	595,395	5.26	258,046	2.11
Self-care									
Same-sex female	16,284	2.63	730	1,201	15,083	17,485	13.45	17,887	2.89
Same-sex male	9,655	1.70	657	1,081	8,574	10,736	20.41	15,956	2.81
Different-sex married	2,296,686	2.05	19,369	31,862	2,264,824	2,328,548	2.53	2,448,072	2.18
Different-sex unmarried	168,201	1.37	2,589	4,258	163,943	172,459	4.62	258,425	2.11

[a] Weighted number of people reporting difficulty with independent living (i.e., "disable")

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

[c] Standard error (SE)

[d] Margin of error (MOE)

[e] Lower confidence limit (LCL): Low limit of 90 % confidence interval = (Disable – MOE)

[f] Upper confidence limit (UCL): High limit of 90 % confidence interval = (Disable + MOE)

[g] Range of uncertainty (RU) = {[(SE × 3) ÷ disable] × 100}

[h] Allocated: Number of responses to 'independent living' survey item which are assigned or changed

[i] Percent allocated (%A) = [(weighted allocated count ÷ weighted total population) × 100] (Note: total population available in Table 1)

Table 3

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

	Disable[a]	%D[b]	SE[c]	MOE[d]	LCL[e]	UCL[f]	RU[g] (%)	Allocated[h]	%A[i]
Cognitive									
Same-Sex Female	26,975	4.36	1,165	1,916	25,059	28,891	12.95	17,915	2.89
Same-sex male	20,403	3.59	904	1,487	18,916	21,890	13.29	15,843	2.79
Different-sex married	3,242,849	2.89	16,309	26,828	3,216,021	3,269,677	1.51	2,420,420	2.16
Different-sex unmarried	438,298	3.58	7,890	12,980	425,318	451,278	5.40	256,926	2.10
Hearing									
Same-sex female	21,497	3.47	1,374	2,261	19,236	23,758	19.18	14,304	2.31
Same-sex male	17,376	3.06	1,195	1,967	15,409	19,343	20.64	12,889	2.27
Different-sex married	4,711,638	4.20	15,607	25,673	4,685,965	4,737,311	0.99	1,996,510	1.78
Different-sex unmarried	268,991	2.20	3,746	6,162	262,829	275,153	4.18	222,753	1.82
Vision									
Same-sex female	12,128	1.96	692	1,139	10,989	13,267	17.13	17,352	2.80
Same-sex male	11,446	2.02	784	1,290	10,156	12,736	20.55	15,233	2.68
Different-sex married	2,094,294	1.87	18,050	29,692	2,064,602	2,123,986	2.59	2,387,349	2.13
Different-sex unmarried	208,517	1.70	4,070	6,696	201,821	215,213	5.86	245,873	2.01

[a]Weighted number of people reporting difficulty with independent living (i.e., “disable”)

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

[c]Standard error (SE)

[d]Margin of error (MOE)

[e]Lower confidence limit (LCL): Low limit of 90 % confidence interval = (Disable – MOE)

[f]Upper confidence limit (UCL): High limit of 90 % confidence interval = (Disable + MOE)

[g]Range of uncertainty (RU) = {[(SE × 3) ÷ disable] × 100}

[h]Allocated: Number of responses to ‘independent living’ survey item which are assigned or changed

[i]Percent allocated (%A) = [(weighted allocated count ÷ weighted total population) × 100] (Note: total population available in Table 1)

Table 4

Percent disable in same-sex couples from top-30 Public Use Microdata Areas

PUMA ID[a]	State	Within County[b]	SS[c]	IL[d]	A[e]	SC[f]	C[g]	H[h]	V[i]
602204	California	San Francisco County	17.7	2.0	1.8	0.5	2.3	1.3	0.9
1100105	DC	District of Columbia	15.5	1.0	1.3	0.0	4.8	0.6	0.5
3603807	New York	New York County	11.4	2.4	3.5	1.6	5.3	1.2	0.9
1301104	Georgia	Fulton County	11.3	1.3	1.7	0.8	2.2	0.8	1.6
1203605	Florida	Broward County	8.1	5.5	5.3	0.0	3.4	4.3	0.7
602203	California	San Francisco County	8.0	4.2	4.8	2.3	3.8	0.0	0.0
608004	California	Riverside County	8.0	4.7	5.8	3.0	2.8	3.7	1.8
1703501	Illinois	Cook County	8.0	4.3	4.0	2.5	3.1	1.8	0.0
3603810	New York	New York County	7.5	1.7	3.6	0.0	3.6	2.8	0.0
4204109	Pennsylvania	Philadelphia County	7.3	0.0	0.0	0.0	1.4	0.0	0.0
2701303	Minnesota	Hennepin County	7.3	0.7	4.2	0.0	0.0	0.0	0.0
4101301	Oregon	Multnomah County	7.2	0.8	3.1	0.0	1.5	1.3	4.1
1301201	Georgia	DeKalb County	6.8	3.6	5.0	1.0	1.8	0.0	1.0
608101	California	San Diego County	6.8	1.6	4.1	0.8	0.6	1.5	0.9
4802301	Texas	Dallas County	6.8	0.0	3.3	1.5	4.2	0.0	1.8
3903105	Ohio	Franklin County	6.3	0.7	4.0	0.7	2.9	3.0	0.9
602403	California	Alameda County	6.1	1.4	2.1	1.4	2.4	1.3	0.0
5301804	Washington	King County	5.7	5.8	5.3	4.1	7.5	0.0	3.0
1204008	Florida	Miami-Dade County	5.5	5.1	8.0	7.0	5.7	8.6	5.5
3603808	New York	New York County	5.5	0.0	0.0	3.5	0.0	1.2	0.9
4101305	Oregon	Multnomah County	5.5	0.0	0.9	0.0	0.7	0.0	0.0
5301803	Washington	King County	5.4	0.0	0.0	0.0	0.0	2.5	0.0
2701301	Minnesota	Hennepin County	5.4	3.3	3.3	0.0	0.0	0.0	0.0
5301805	Washington	King County	5.4	0.9	3.4	1.2	2.2	1.0	0.0
2503305	Massachusetts	Suffolk County	5.3	1.9	0.7	0.7	1.9	0.0	0.7
602205	California	San Francisco County	5.2	3.3	5.8	0.0	1.2	3.4	0.0

PUMA ID[a]	State	Within County[b]	SS[c]	IL[d]	A[e]	SC[f]	C[g]	H[h]	V[i]
3603803	New York	New York County	5.2	1.1	5.7	5.7	1.1	0.0	0.0
2400805	Maryland	Baltimore City	5.1	0.0	0.0	0.0	0.0	0.0	0.0
4802302	Texas	Dallas County	5.0	6.4	6.3	3.5	5.8	0.0	1.1
2503302	Massachusetts	Suffolk County	5.0	4.2	5.8	3.1	4.8	3.7	0.0

[a] Public Use Microdata Area identification number

[b] PUMA is located within the geographical boundaries of this county

[c] SS = % of all couples from PUMA in same-sex relationship

[d] IL = % with independent living difficulty

[e] A = % with ambulatory difficulty

[f] SC = % with self-care difficulty

[g] C = % with cognitive difficulty

[h] H = % with hearing difficulty

[i] V = % with vision difficulty