**Trends in Behavioral Health Service Utilization among US adults before and during the COVID-19 pandemic**

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**INTRODUCTION:**

**Background:**

The COVID-19 pandemic deeply impacted people across the globe in a variety of ways. The virus itself and its infectiousness created newfound anxiety due to the fear of infection from the potentially life-threatening condition (Uwadiale, *et al.*, 2022; Rea 2021). In addition, the public health measures that sought to prevent further infection, such as stay-at-home orders, further increased feelings of loneliness and isolation that are associated with further mental health concerns (Ammerman, *et al.,* 2021). The pandemic’s economic impacts on employment and income were felt globally but in disparate ways by race, socioeconomic status, education, gender, age, sexual orientation, and disability status (Le, *et al.* 2021; Tsai, *et al.*, 2021).

These impacts have been linked to increased mental health symptoms in US adults. Several studies have noted these impacts on depression and anxiety in US adults (DiClemente, *et al.,* 2022; Breslau, *et al.*, 2022). One study found an 88% increase in mental health need among US adults utilizing primary care services compared to pre-pandemic levels (Britz, *et al.*, 2022). Among a large representative sample of US adults, the number of adults diagnosed with anxiety increased significantly early in the pandemic compared to pre-pandemic levels (Valdes, *et al.,* 2022; Uwadiale, *et al.,* 2022). These point to an increased need for mental health services among US adults.

This increase in need is noted among US adults generally as well as by specific minority populations. In particular, studies found strong disparities in impact by gender, age, socioeconomic vulnerability, insurance, and racial/ethnic identity. Younger individuals such as those age 18-30 were found to report higher levels of mental health distress (Breslau, et al, 2022; Reading, *et al.,* 2021). Black Americans, Hispanic Americans, Asian American, and mixed-race Americans were noted to have higher odds of experiencing depression compared to White Americans accounting for other socioeconomic and historical factors (Breslau, *et al.*, 2022; Nguyen, *et al.,* 2022; Liu, *et al.,* 2021). Those at the highest levels of socioeconomic vulnerability were noted to have the highest levels of mental health distress (Brooks, *et al.*, 2022; Griggs, *et al.*, 2022; Osaghe, *et al.*, 2021).

While need clearly increased, there is varying evidence of the impacts of the COVID-19 pandemic on utilization. Several public health measures aimed to restrict the utilization of in-person health services, but there was still access to other sources of mental health care such as ER utilization, primary care telehealth appointments or outpatient counseling. One study found those with more severe depression symptoms were moderately to severely impacted in their ability to access mental health treatment, food resources, and income (Sanchez, *et al.,* 2022). While ED utilization during COVID-19 mitigation measures decreased, one study found an increase in utilization for substance use including opioid use disorder (Holland, *et al*., 2021). Older adults during the pandemic also faced significant difficulties and barriers to accessing mental health services and treatment due to COVID-19 public health protocols, which can also relate to their experiences of mental health symptoms (Carpenter, et al., 2022; Martin, et al., 2022). Service utilization between physical and mental health needs experience differing barriers but may still be affected by some similar systemic issues. In understanding this, one study explored factors for forgoing and delaying medical care. Some of these factors that negatively impacted the accessibility of medical services included severe mental illness, insurance status, and length of exposure to the COVID-19 pandemic (Giannouchi, et al., 2022; Holland, et al., 2021; Jalan, et al., 2022).

Given the clear evidence of mental health impacts of COVID-19, there is limited understanding of how these mental health needs of the pandemic have been addressed. In this study, we aim to address the limited understanding of how mental health needs are met in a nationally representative sample. We additionally explore the differences in mental health utilization by population subgroup, including gender, race, education, income, and age.

**Aims:**

The aim of this study is to evaluate changes in mental health-related service utilization based on need, associated with the COVID-19 pandemic in the United States. We try to answer the following questions:

* RQ1: The period during COVID-19 pandemic was associated with a higher proportion of individuals having serious psychological distress, compared to the prior periods.
* RQ2: The period during COVID-19 pandemic was generally associated with lower service utilization for behavioral health, compared to the prior periods.
* RQ3: Over the COVID-19 period, having serious psychological distress was associated with lower behavioral health service utilization, compared to the prior periods.

**METHODS**

**Study Design and Population**

The Medical Expenditure Panel Survey is a nationally representative sample of US non-institutionalized population and provides key estimates on health care use (both frequency and type), expenditures across care types, payment sources, and coverage of health insurance that is representative of the population.[[1]](#footnote-2),[[2]](#footnote-3) The individual-level panel design of the survey allows for the assessment of changes in cost, utilization, insurance, and income variables over two-three years generally (with the exception of Panel 23, which spanned four years). The survey however also allows annual cross-sectional assessments across different rounds of panels. As such, the samples are selected through a clustered-random sampling method. Importantly the MEPS sample involves sampling from the households participating in the previous year’s National Health Interview Survey (NHIS) conducted by the National Center for Health Statistics.

The data are collected using the Computer Assisted Personal Interviewing (CAPI) design, where information about each household member is collected. Though, only one respondent per household provides data for all the members of the household. Once the household component is completed, and after receiving consent to do so, a sample of medical providers are contacted over the phone to receive information about conditions, visits, and expenditures; these are considered to be more accurate than the ones reported by the household and are thus relied upon for information on service utilization. These data are collected under the Medical Provider component or the Pharmacy Component of the surveys. These data also include important features such as ICD-10 codes for conditions, service utilized for each person, for each condition, as well as National Drug Codes to help with classification of the medications used. All in all, these aspects make the MEPS a very rich source of data for our analysis. [[3]](#footnote-4)

Each year’s cross-sectional dataset consists of about 15,000 households, while the panel consists of only a fraction of individuals followed anywhere between 5 and 9 rounds of data collection. For the purposes of this study, we will consider the annual data files before (2018, 2019) and during the COVID-19 period (2020, 2021), to assess changes in service utilization based on associated need across these periods. We will also consider assessing changes in need and service use over time for a panel of individuals that were followed between 2018-2021 (Panel 23).

**Data Sources**

We will use four sets of files for this analysis: 1) the **MEPS Full-year Consolidated files (2018-2021)[[4]](#footnote-5)**, which include annual demographics and service use measures, 2) the **MEPS Medical Conditions files (2018-2021)[[5]](#footnote-6)**, which include the person-diagnosis level counts for each type of visit (in-patient, out-patient, home health, emergency room, office-based) associated with specific diagnosis, as measured through the tenth version of the International Classification of Diseases codes (ICD-10), 3) the **MEPS Event-level Files (2018-2021)**[[6]](#footnote-7), which include event-level estimates of types of visits (in-patient, out-patient, home health, emergency room, office-based), along with associated costs and some information on visit characteristics (including type of provider seen, etc.) for certain types of visits, and 4) the **MEPS Longitudinal Files for Panel 23 (2018-2021)** which comprises of all the data collected for individuals who were a part of Panel 23, with over 9 rounds of data collection.

We utilize both the repeated cross-sectional files as well as the panel data files to a) evaluate changes at each point in time for the three research questions, and b) to evaluate whether there were changes in outcomes within individuals over time. We use the former because these files also include harmonized annual estimates for several variables which may not be easily available in the longitudinal files. Moreover, these files combine data from other panels that were run at the same time, allowing for a larger sample size compared to a single panel of individuals.

That said, service utilization may be correlated with having any pre-existing mental health condition, and also with the types of pre-existing conditions (long-term versus short-term), and so we suspect that only looking at trends cross-sectionally can bias the estimates just based on the sample composition. Moreover, since Panel 23 was unique in that it contains data for four years, it is hard to merge these data with other panels due to a) the number of years that the data were collected for this panel, and b) due to the changes in data collection techniques over time that may have impacted this panel differently, compared to others. While the latter is an important limitation of this dataset, it still is plausible to use it for evaluating relationships over time.

For the purposes of this class, I cleaned up the prior code for the preparation and analysis of the repeated cross-section files, and prepared the longitudinal files for analysis. The sections below describe the steps we plan to take to complete the analysis for this paper. There is a lot that still needs to be thought through, especially with the use of the longitudinal files, so consider this a working document with scope for tons of improvements!

**Measures**

***General measures of interest***

Our main independent variable is the psychological distress score, measured through the Kessler-6 scale (K-6) scale, and offered as part of the Self-Administered Questionnaires (SAQ) module of the MEPS. This scale was selected based on prior literature concerning the measurement of non-specific psychological distress. The scale includes six items related to constructs associated with psychological distress, including how often the respondent felt the following over the last 30 days: i) nervous, ii) hopeless, iii) restless or fidgety, iv) so sad that nothing could cheer the person up, v) that everything was an effort, and vi) worthless. The response scale for each item range from 0 = *None of the time*, to 4 = *All of the time*. A sum of the items is included in the public dataset (the values ranging from 0-24), and a binary variable indicative of serious psychological distress (K6-score of 13 or higher) was derived for analysis. This variable was collected at rounds 2, 4, 6, and 8 that was administered to all in-scope adults in the panel file, and are summarized for each year within the full-year files.

Another set of independent variables of interest for our analyses include a categorical variable indicating the survey year (2018, 2019, 2020, or 2021), and a binary variable indicating whether or not the period included COVID-19 related shocks (0 = 2018, 2019; 1 = 2020, 2021). We additionally include a series of respondent-specific control variables, i.e., demographics (age, gender, level of education, marital status, insurance status [insured/uninsured], annual household income as a percentage of poverty line, race), geographic region of residence at the time of the survey, and general health status (including whether or not the respondent had received a diabetes, arthritis, or cancer diagnosis at the time of the survey).

***Outcome measures***

Our study intends to review changes across two broad categories of outcomes:

1. *Behavioral health-related service utilization* which will be assessed using the counts of different types of visits (including office-based visits, in-patient visits, outpatient visits, and emergency room visits), and number of prescribed medications associated with the ICD-10 codes ranging from F1-F99
2. *Behavioral health-related total annual expenditures* were computed at person-ICD-10 level by adding visits-related expenditures and prescription expenditures over the year, for each person-ICD-10 pair for ICD-10 of F1-F99. To ensure comparability across periods, the total expenditures for 2019, 2020 and 2021 were converted to 2018 United States Dollars (USD).

We will also evaluate differences in service use and expenditures by different types of mental health conditions as a secondary analysis (as described below), to see if there is heterogeneity in the relationship between different types of mental health conditions.

**Data Preparation**

***Full-year consolidated dataset***

To begin, we combined the demographics and independent variables from the Full year consolidated files, with the corresponding year’s Medical Conditions and Event-level visit files. We appended these files to create the final dataset. We additionally included the pooled variance estimates made available through the MEPS Pooled Linkage Variance Structure and BRR (1996-2020)[[7]](#footnote-8) file. For the purposes of our analysis, we excluded individuals who were less than 18 years of age, and those that did not have a K-6 score value or unavailable physical or mental health measure. This meant that our analysis considered those that responded to the Self-Administered Questionnaire. ***Table 1*** shows the breakdown of the exclusion criteria and the number of observations in the final dataset for the repeated cross-section (full-year) data.

An important feature of the Medical Conditions and Event-level files is that they only contain data if there were any reported events or services utilized pertaining to a particular ICD-10 during that year. We utilized this to keep all person-ICD-10 observations pertaining to ICD-10 values ranging from F1-F99. Additionally, to ensure that all the eligible participants remain in the dataset, even if they had no service or expenditures associated with behavioral health, their visit and expenditures were set to 0. We additionally categorized age, marital status, education status, income (non-negative), and poverty level (family income as a % of poverty). Moreover, given that the files only contained a small subset of F-level ICD10 codes, a categorical variable for mental health category was defined as follows:

* F10-F19: substance-induced mental health conditions
* F03, F20-F43: non-substance, adult-onset disorders
* F80-F91: childhood-onset mental health disorders
* F51, F99: other conditions

Finally, total expenditures for conditions were calculated as the sum of the expenses for all visit types.

***Longitudinal dataset***

For the longitudinal dataset, we first prepared all the medical conditions and event files to create a person-round-icd10-eventtype level dataset; this was then collapsed to the person-round level data, with summed visits and expenditures for different visit types and mental health conditions. We plan to do the same processes as in the preparation of the full-year consolidated dataset, with only one difference – we will create a person-round level file (with rounds 1-5 signifying the pre-period and rounds 6-9 signifying the post period) with the longitudinal file, rather than a person-year level file over different panels. Importantly, to preserve the sample size, we will keep responses for all participants, as long as they responded to at least one SAQ survey in the pre period and at least one SAQ round in the post period. Though, as with above, we will exclude participants who were younger than 18 years of age at round 1.

**Data Analytic Procedures**

***Repeated cross-section files***

We will first calculate the descriptive statistics on the general demographic distribution of the sample (including age, race, gender, education status, family bracket (based on % poverty), insurance status (in terms of full year coverage), marital status, presence of cognitive and social limitations, perceived mental health, perceive physical health, and presence of comorbidities in rounds 1-5 for the longitudinal panel, and over 2018-2019 period (pre-covid).

To begin, we will fit logit regression models assessing changes in the log odds of serious mental distress in 2019 and 2020, compared to 2018, and the log odds of serious mental distress during COVID-19 period, compared to pre-COVID-19. We will additionally fit logit regressions to assess changes in log odds of seeking any behavioral health services in 2019 and 2020, compared to 2018, and the log odds of seeking any behavioral health service during the COVID-19 period, compared to the pre-COVID-19 period. All models will consider an unadjusted and an adjusted specification. We will use Hosmer-Lemeshow test to assess model fit; a non-significant F-value (at ) is indicative of a good model fit.

Counts of each type of visit and number of prescribed medications for behavioral health (i.e., the outcome variables assessing *behavioral health-related service utilization*) will be modeled with two different specifications – 1) evaluating changes in service use across those with severe mental distress over the 2019 and 2020 periods, compared to those with low to moderate mental distress in 2018, and 2) evaluating changes in service use across those with and without several mental distress during COVID-19 compared to the pre-COVID-19 period. Since all the outcome variables were generally overdispersed at 0, the model specification for each will be identified by comparing model fit parameters (AIC, BIC, and log likelihood) across six different models – poisson, negative binomial (2), negative binomial (1), hurdle poisson, hurdle negative binomial, zero-inflated poisson, and zero-inflated negative binomial. We will additionally compare model fit by plotting the distributions of predicted versus actual values of the outcomes across each model specification. The model with the lowest values across at least two of the three metrics, as well as the one with the closest predicted distribution compared to the actual outcome distribution will be used for final assessment. All final models will include an unadjusted and an adjusted specification.

*Behavioral health-related total annual expenditures* outcome variable is heteroskedastic and overdispersed at 0. Literature suggests two ways to correct for this: 1) a natural log transformation of this outcome measure generally achieves normality, and 2) the use of Generalized Linear Model (GLM) provides the required flexibility of selecting different link functions and modeling functions to account for heteroskedasticity while accurately capturing the mean of the distribution. However, to additionally account for the overdispersion, we will build a two-part model where the first part models the probability of incurring any healthcare expense (the process of positive value generation), and the second part models the “positive” expenditures incurred. To model this, we will first run a Boxcox test to identify the best transformation of all positive expenditure values, and check for its validity by running the test with and without covariates and comparing the value of the resulting lambda. Lambda estimates the power that can be used for the transformation (e.g., a value closest to 0 translates to a natural log transformation, a value closest to 1 translates to a linear transformation, while a value closest to 0.5 translates to a square-root transformation). Based on the results, we will estimate a two-part model, with a logit for the first part of the model and a GLM for the second part. As GLM provides several different functions for model fitting, we will use the Park test to assess which model shows the best fit prior to estimating the final two-part model. We will also run the Link test to ensure that the logit part of the model was a good fit.

Once the models have been identified, we will use those to assess heterogeneity in relationships between severe mental health distress and the outcomes based on insurance status, type of pre-existing mental health condition (if any), age, gender, and income.

For all the models, we will use the linearized Taylor-series estimation method along with sampling weights and pooled sampling variance estimates, as was recommended by MEPS, to account for the complex data-collection design. Given MEPS’ complex survey design, as well as our inclusion criteria that primarily accepts the K6 scores, we will use the Self-Administered Questionnaire weights (adjusted for the number of years included) for our analysis, along with the pooled variance estimates made available through the MEPS Pooled Linkage Variance Structure and BRR (1996-2020)[[8]](#footnote-9) file.

***Longitudinal assessment***

The longitudinal dataset will be used to assess changes over time for the same set of individuals. This means that the model will follow a difference-in-difference type event study design. For this assessment, we will evaluate changes to K-6 values over rounds, and over the pre- and post-COVID period for each individual, and then assess a) whether going from pre to post, more individuals show severe mental distress, b) conditional on having severe mental distress, whether mental health services are utilized based on need going from pre- to post-, and c) there is heterogeneity in mental health needs and severe mental distress based on any pre-existing mental health condition.

For each outcome variable, we will consider the parallel trends assumption, meaning that in the absence of COVID-19, the trends in the outcome between those with severe mental distress and those without severe mental distress would have been the same. Thus, we will use ordinary least squares regressions/linear probability models (along with logit, poisson and/or negative binomial as secondary specifications, depending on the outcome) to evaluate how the number of visits for mental health, and the corresponding expenditures, change over time in the pre-period. We will also plot the trends over rounds to identify any non-common shocks. While all these assessments are important from the causal inference stand point, evaluating them for our purposes can be helpful to control for time varying confounders.

To help control of time invariant confounders, our models will involve the use of person fixed effects. The standard errors will be handled in the same way as the repeated cross-section files, as will be the use of sampling weights for our analysis.

**Limitations:**

Our analysis has several key limitations related to the data sources available given the difficulty of research, and in particular, survey research, during the pandemic. MEPS 2020 reported a non-response bias “specifically, that households in higher socio-economic levels were relatively more likely to respond and the sample weighting was unable to fully compensate for this.” This bias is likely related to delay in panels caused by the pandemic which created longer recall for those in 2020. In addition, the transition from in-person to telephone interviews strongly biases towards those with access to phones and in particular those who are likely higher income. The spread of mistrust in telephone surveyors and the widespread scams that occur via phone have made many individuals less willing to participate in phone interviews. Finally, there is a CPS bias which impacts the weights used by the MEPS dataset (Agency for Healthcare Research & Quality, 2022). While we expect that the use of the same panel for data collection may have helped counter this possible bias, our results will still be limited in generalizability due to the focus on those who were available and able to access and respond to the surveys virtually.

Secondly, given the tumultuous nature of the COVID-19 pandemic on individuals’ lives and on the ability to conduct research, there is need to accurately and critically capture trends in service utilization and mental health need over time to assess differences over time. Towards this goal, our work only can begin to look at these trends since only data through 2021 was available. Our analysis is limited to four years – two that were pre-pandemic, and two that were around the pandemic period. While that is a sufficient time to carry out a pre-post analysis, it would be useful to increase the observation period to include a few more years prior, and several years after as the data becomes available to get a more accurate picture of the changes in utilization post the pandemic.

Additionally, COVID-19 may have increased the use of digital care services, which may not have costed much – so we expect the comparability of expenditures and visits to be lower compared to the pre-pandemic years. MEPS has included questions about seeking digital care but we don’t have information on how different this was from the pre-pandemic years, since these questions are only asked in 2020 and 2021, and thus render them incomparable for the purposes of our analysis.

Finally, given the design of the MEPS surveys, we are unable to rule out the possibility that visits were overcounted in some cases, because more than one conditions could have been examined/evaluate during the same visit.

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**TABLES**

**Table 1:** Exclusion criteria, and the corresponding dropped observations to carry out a complete analysis.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Exclusion Criteria** | **2018** | **2019** | **2020** | |
| Total values | 30,461 | 28,512 | 27,805 |
| Excluded: <18 years | 7,434 | 6,547 | 5,926 |
| Excluded: unavailable K-6 score values | 4,194 | 4,727 | 7,817 |
| Excluded: unavailable Physical health measure | 5 | 8 | 7 |
| Excluded: unavailable Mental health measure | 6 | 3 | 9 |
| Final included in the analysis | 18,822 | 17,227 | 14,046 |

**APPENDIX**

**Appendix-A: Participant characteristics over 2018-2020**

|  |  |  |  |
| --- | --- | --- | --- |
| **Sample Characteristics** | **2018** | **2019** | **2020** |
| N (%) Mean (SD) | N (%) Mean (SD) | N (%) Mean(SD) |
| Total distinct respondents (N) | 18,366 | 16,817 | 13,665 |
| **Gender** |  |  |  |
| Male | 8426 (48.12) | 7770 (48.33) | 6125 (48.13) |
| Female | 9940 (51.9) | 9047 (51.67) | 7540 (51.87) |
| **Age** |  |  |  |
| 18-39 | 6289 (38.22) | 5431 (37.86) | 3716 (37.33) |
| 40-59 | 5984 (32.59) | 5494 (33.25) | 4291 (32.49) |
| 60-85 | 6093 (29.19) | 5892 (28.88) | 5658 (30.18) |
| **Race** |  |  |  |
| Caucasian | 13936 (77.65) | 12960 (78.07) | 10724 (78.50) |
| African American | 2745 (12.22) | 2323 (11.82) | 1724 (11.96) |
| American Indian/Alaskan Native | 133 (0.69) | 139 (0.77) | 114 (0.82) |
| Asian/Native Hawaiian/Pacific Highlander | 1009 (6.64) | 938 (6.68) | 762 (6.38) |
| Multiple Races | 543 (2.80) | 457 (2.66) | 341 (2.34) |
| **Education Level** |  |  |  |
| Less than High School | 2838 (11.74) | 2489 (12.23) | 1895 (12.16) |
| High School Certificate | 5626 (27.16) | 4977 (26.82) | 3905 (27.46) |
| Some college or higher | 9902 (61.1) | 9351 (60.94) | 7865 (60.38) |
| **Family Income as % Poverty Ratio** |  |  |  |
| Poor/Negative | 2653 (10.08) | 2340 (10.08) | 1785 (9.57) |
| Near Poor | 843 (3.76) | 778 (3.67) | 610 (3.34) |
| Low Income | 2524 (11.77) | 2274 (12.01) | 1915 (11.44) |
| Middle Income | 5308 (28.94) | 4817 (28.98) | 3710 (28.08) |
| High Income | 7038 (45.44) | 6608 (45.25) | 5645 (47.57) |
| **Perceived Health Status (last round)** |  |  |  |
| Excellent | 3922 (23.69) | 3558 (23.56) | 2777 (23.36) |
| Very Good | 6138 (35.27) | 5819 (36.56) | 4706 (36.00) |
| Good | 5676 (29.18) | 5048 (28.21) | 4215 (29.12) |
| Fair | 1962 (9.09) | 1855 (9.28) | 1566 (9.72) |
| Poor | 601 (2.78) | 478 (2.38) | 338 (1.91) |
| **Insurance Status** |  |  |  |
| < 65 years and any private | 9502 (59.34) | 8589 (59.13) | 6432 (57.57) |
| < 65 years and public only | 2796 (12.32) | 2488 (12.73) | 1943 (12.93) |
| < 65 and uninsured | 1538 (7.49) | 1342 (7.31) | 987 (7.54) |
| 65+ Medicare only | 1524 (7.15) | 1595 (7.58) | 1624 (8.25) |
| 65+ Medicare and private | 2164 (10.51) | 2034 (10.04) | 1943 (10.52) |
| 65+ Medicare and other public only | 770 (2.85) | 708 (2.92) | 671 (2.79) |
| 65+ and uninsured | 24 (0.07) | 17 (0.07) | 15 (0.08) |
| 65+ and no medicare and any public/private | 48 (0.25) | 44 (0.23) | 50 (0.33) |
| **Marital Status** |  |  |  |
| Married | 9006 (48.08) | 8201 (47.65) | 6804 (47.94) |
| Not Married | 9360 (51.92) | 8616 (52.35) | 6861 (52.06) |
| **Psychological Distress Score** |  |  |  |
| No Major Distress (K6 < 13) | 17594 (93.76) | 16104 (93.44) | 13042 (92.35) |
| Major Distress (K6 >= 13) | 772 (6.24) | 713 (6.56) | 623 (4.12) |
| **PHQ2 Score** |  |  |  |
| Does not show signs of major depressive disorder (PHQ2 < 3) | 16997 (93.76) | 15547 (93.44) | 12530.00 |
| Shows signs of major depressive disorder (PHQ2 >= 3) | 1369 (6.24) | 1270 (6.56) | 1135 (7.65) |

1. https://meps.ahrq.gov/data\_stats/download\_data/pufs/h224/h224doc.pdf [↑](#footnote-ref-2)
2. https://meps.ahrq.gov/mepsweb/about\_meps/survey\_back.jsp [↑](#footnote-ref-3)
3. https://meps.ahrq.gov/data\_stats/download\_data/pufs/h224/h224doc.pdf [↑](#footnote-ref-4)
4. That includes h209, h216, h224 [↑](#footnote-ref-5)
5. That includes h207, h214, h222 [↑](#footnote-ref-6)
6. That includes h220a h220d-h, h213a, h213d-h, and h206a, h206d-h. [↑](#footnote-ref-7)
7. That includes HC-036 [↑](#footnote-ref-8)
8. That includes HC-036 [↑](#footnote-ref-9)