Appendix for "SMALL AREA ANALYSIS OF VA MENTAL HEALTH SERVICES DATA**"**

In this appendix, we provide additional details and results to supplement the main text of our paper for interested readers. The appendix is divided into three sections: 1) Definitions used to identify mental health visits; 2) Description of MHSAs and MHRRs; 3) Calculation of the localization index and results of sensitivity analyses and 4) Examples of attribution with low and high localization.

Section 1: Definitions used to identify mental health visits.

We constructed regions using mental health care that was provided by the VHA. We did not include contracted or other VA purchased care. The VHA provides a wide range of mental health services including integrated primary care mental health, general outpatient mental health, outpatient substance use treatment, residential rehabilitation including residential substance abuse treatment, psychosocial residential rehabilitation, PTSD treatment, supported employment programs, homeless services, and acute mental health service (29). The VA often uses its own system for identifying the type of care provided. While the Healthcare Common Procedure Coding System (HCPCS) codes are used, stop codes provide a primary means to identify certain types of care delivered by the VA. We have provided below a list of codes that were used to define outpatient mental health visits. We accepted any record with one of these stop codes in the primary or secondary position. We allowed only a single visit per day per person.

Stop Codes: 292, 502, 503, 504, 505, 506, 507, 508, 509, 510, 511, 512 , 516, 519, 522, 524, 525, 529, 531,532, 533, 534, 535, 539, 540, 550, 552, 553, 554, 555, 556, 557, 558, 561, 562, 564, 565, 567, 568,571, 572, 573, 574, 575, 576, 577, 582, 583, 586, 587, 588, 590, 591,592, 593, 595, 596, 598, 599
For descriptions of stop codes see http://vaww.dss.med.va.gov/programdocs/pd_oident.asp

While the stop codes used typically define visits to actual facilities, the other stop code can provide additional detail such as telehealth. We evaluated the existence of telehealth among the visits selected over time. We found that telehealth visits comprised a very small fraction of all selected mental health visits (i.e. 0.9% of visits in 2008 which rose slowly rose to 1.9% by 2014). Furthermore, even in 2018 we found only 2.2% of visits used telehealth.

Section 2: Definitions and descriptions of MHSAs and MHRRs

We defined MHSAs and MHRRs around specific facilities. Once created, the areas represent groups of counties (and veterans who live within them) and are used to compare outcomes. There are different ways to describe the size of each service area. The main paper describes the number of MHSAs and MHRRS, the number of counties per MHSA and the number of MHSAs per MHRR. Here, we provide more details about the number of patients per region, where a patient is any Veteran who had at least one outpatient mental health visit.

The following table is based on 2008-2014 and we only count each Veteran once.

Region		# of veterans attributed to each region						
Type	N (# of areas)	Min	Max	Mean	SD	Median	25%	75%
MHSA	441	23	93,579	9,481	12,010	4,617	1,633	12,656
MHRR	115	280	129263	35,772	23,725	30,049	17,322	45,599

We note one MHSA had only 23 veterans who accessed mental health care and 25% of MHSAs had <1633 people. These relatively small numbers explain why we chose counties instead of zip codes to create service areas: N's at the zip code level would often be too low and instable.

Section 3: Calculation of the localization index and results of sensitivity analysis

Calculation of localization index

We allocated counties to MHSAs by evaluating the localization index. As we created maps showing the location of specific facilities, we calculated localization to specific facilities. In the main paper, we describe localization using the strictest definition: the fraction of visits from veterans in an area that used the facility that defines the area. In this appendix, we also report findings using a more typical definition of localization that includes the fraction of visits to all facilities in an area divided by all visits from patients. In our main analysis, we chose to use the stricter definition of localization for several reasons. First, the maps we generated and spreadsheets containing localization values showed specific facilities. Second, we want the tools that we have created to be meaningful to local administrators: naming areas based on the primary facility provides that context.

The following is a list of the calculations for localization.

Localization (strict) = (visits to one facility) / (visits to all facilities).

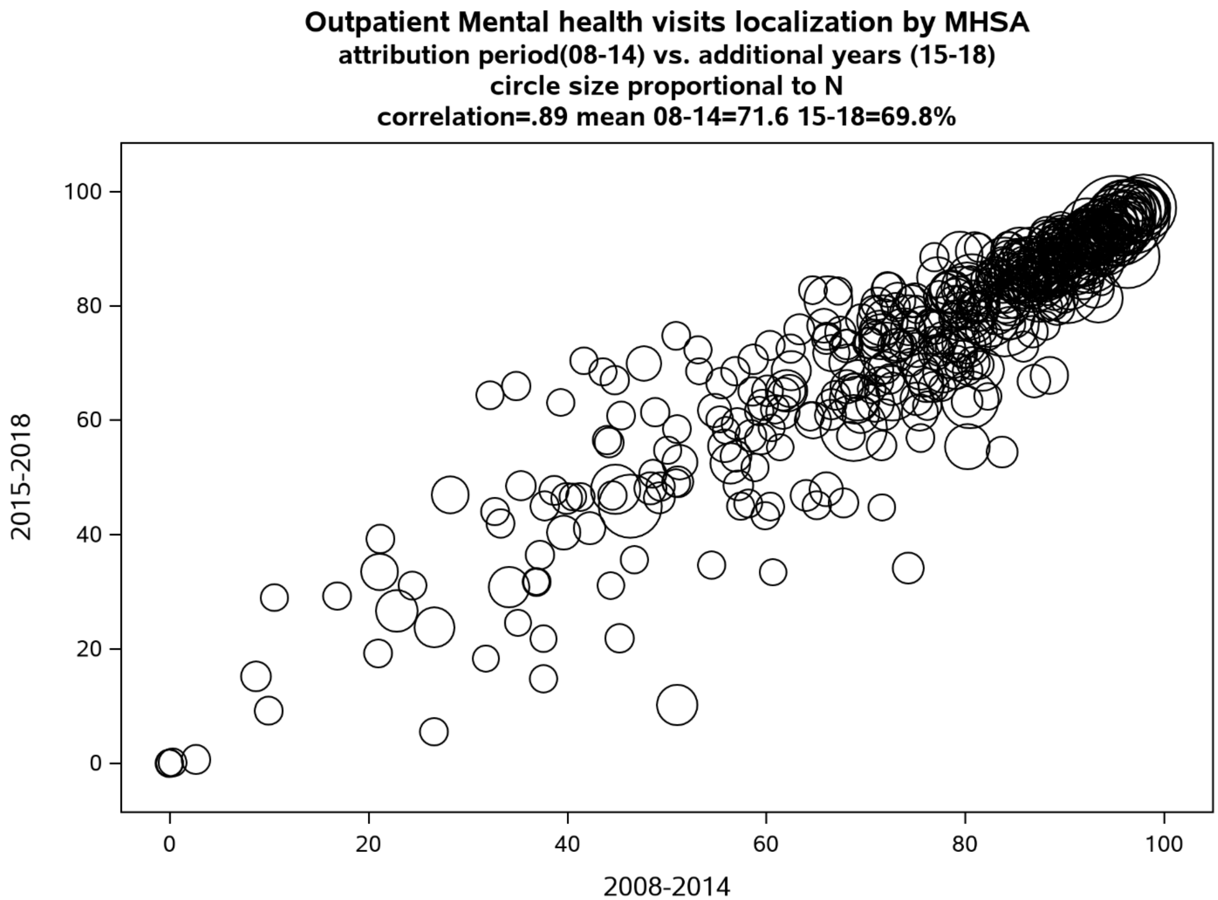
Localization (typical) = (visits all facilities in MHSA) / (visits to all facilities).

As shown below under "results of sensitivity analysis," the first figure shows the results of localization using the stricter definition, while the second figure shows the results using a more typical, area level definition. We note that the localization goes from ~70% to over 90% by shifting from the strict to more typical methodology and provides even stronger evidence that our service areas are valid and appropriate.

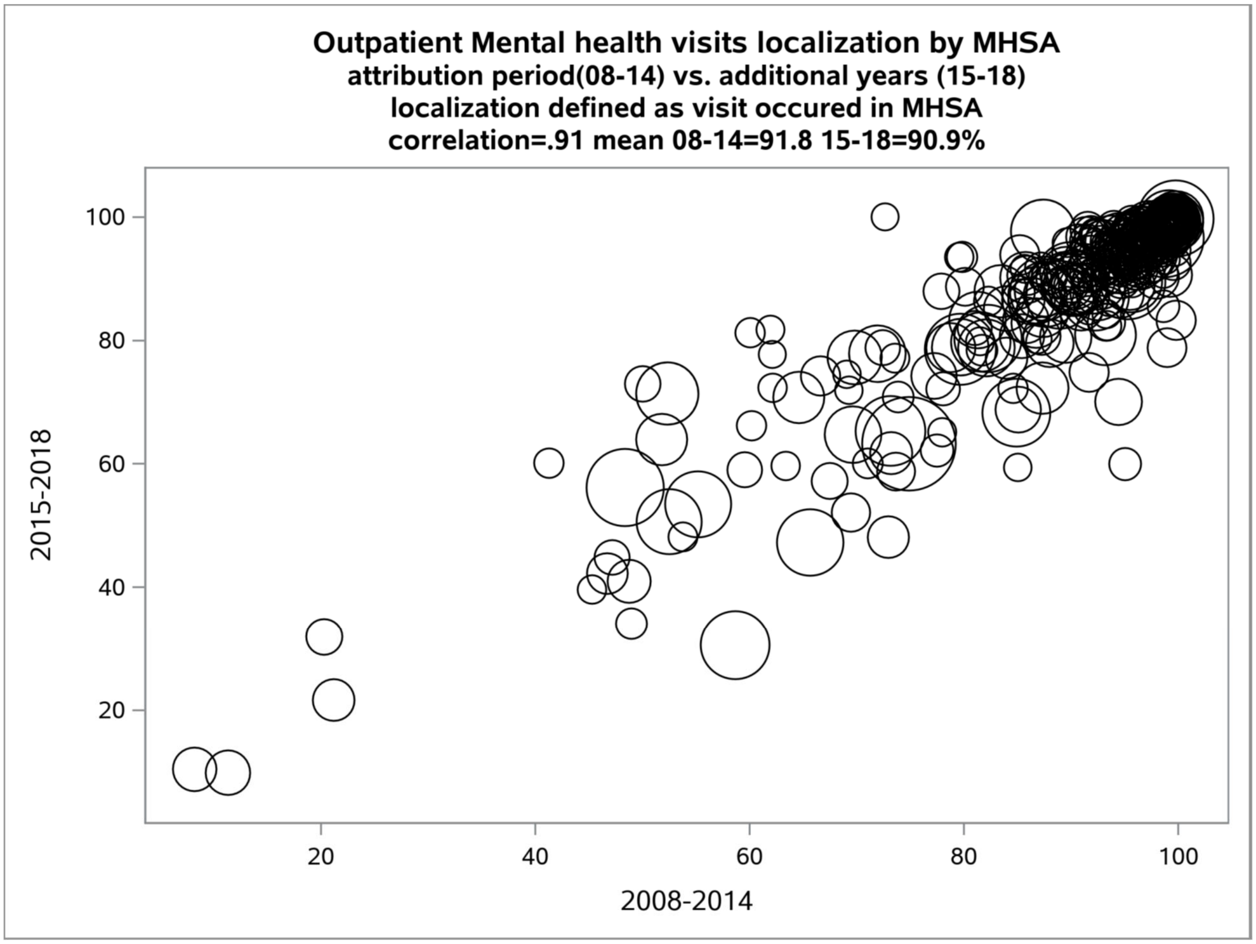
Results of sensitivity analysis

We used care received from 2008-2014 to perform our attribution and care received from 2008-2018 to evaluate outcomes. We made this decision because we initially only had a data use agreement (DUA) covering the earlier period. To determine how sensitive the attribution was to changing time periods, we first calculated the localization in each region (MHSA/MHRR) using the two different time periods. We then calculated the mean values and their correlation. Finally, we plotted the results.

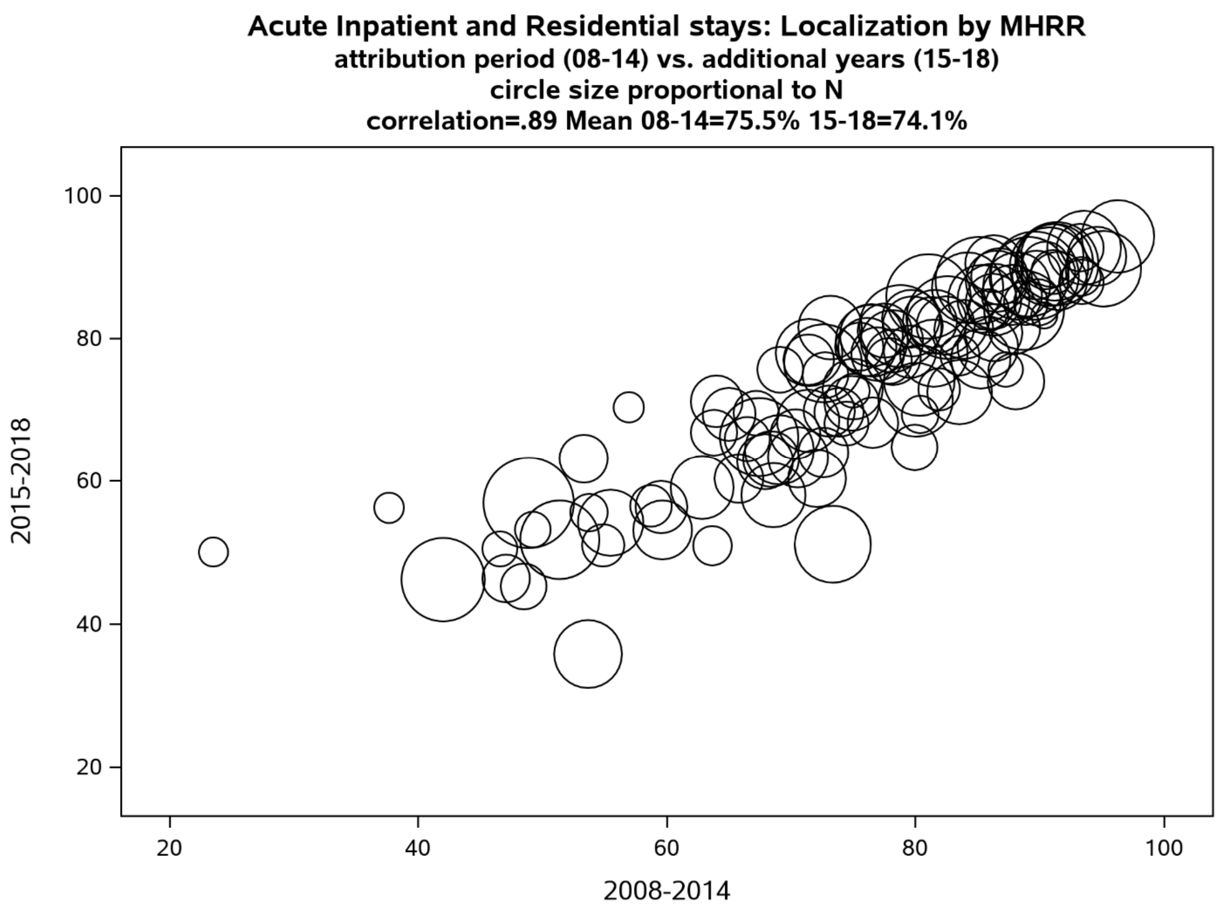
As shown below, the first figure shows the localization for outpatient mental health visits at the MHSA level. It demonstrates a very high correlation (0.89) and similar mean values in the two time intervals. As described above, the second figure calculates localization in the more typical fashion by combining facilities within each MHSA. While we note that the localization jumps to over 90% in the second figure, the correlation between the two time periods remains high at 0.91. Overall, these findings suggest that the attribution is quite stable over time. Furthermore, the third figure shows that based on Acute and Residential stays at the MHRR level, there was also a very high correlation (0.89) between localization at each time period and similar localization values, indicating that the attribution is stable over time. The stricter definition of localization was used- only small changes were noted when using the more typical, area wide definition since many MHRRs have only one facility that does inpatient mental health stays.



Correlation between outpatient mental health visit localization by MHSA attribution period (2008 – 2014) versus additional years (2015 – 2018). In this figure, localization index is based on the stricter definition of the fraction of visits from veterans in an area that used the facility that defines the area._



Correlation between outpatient mental health visit localization by MHSA attribution period (2008 – 2014) versus additional years (2015 – 2018). In this figure, localization index based on a more typical definition of the fraction of visits to all facilities in an area divided by all visits from patients.



Correlation between acute inpatient and residential stays localization by MHRR attribution period (2008 – 2014) versus additional years (2015 – 2018).

In this figure, localization index is based on a stricter definition of the fraction of visits from veterans in an area that used the facility that defines the area, though the results are very similar when using the more typical definition.

Section 3: examples of areas with low and high localization

As described in the text our primary means for attributing areas to a region was via the localization to a specific facility residing in that region. In most cases the algorithmic approach worked quite well as veterans living in an area tend to seek care near where they live. In some instances, localization to the local facility was quite low and we would not allow an area to be assigned to some distant region. We provide a few examples.
Alaska is of course a large, sparsely populated state. There are few VA facilities that provide inpatient mental health care in the state, though there is a VAMC in Anchorage that does. We found that residents in and around Anchorage had fairly high localization to that facility though a fair number used a facility in Washington State. Among much of central and northern Alaska the localization algorithm attributed regions to the same facility in Washington State. We forced these MHSAs to be attributed to the Anchorage MHRR to require continuity of regions.

We also noted not surprisingly that relatively rural regions with a VAMC nearby tended to have high localization to that facility. For instance, the Fresno area MHSA was attributed to the Fresno MHRR with 89% localization. Similarly, in the Sierras of CA the localization was 87% for the local VAMC.

Areas that are roughly equidistant to multiple facilities tended to have localization split evenly between the two facilities. For instance, residents of northern Florida tended to use both the North Florida/South Georgia facility as well as the Gulf Coast Health Care Center roughly equivalently. Similarly, in southern New Jersey we note ~40% of inpatient stays occurred at a facility in southern NJ and another in Philadelphia.