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# County-Level Concentration of Selected Chronic Conditions Among Medicare Fee-for-Service Beneficiaries and Its Association with Medicare Spending in the United States, 2017

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## Abstract

Multiple chronic conditions (MCC) reduce quality of life and are associated with high per capita health care spending. One potential way to reduce Medicare spending for MCC is to identify counties whose populations have high levels of spending compared to level of disease burden. Using a nationally representative sample of Medicare Fee-for-Service beneficiaries, this paper presents a method to measure the collective burden of several chronic conditions in a population, which the authors have termed the concentration of chronic conditions (CCC). The authors observed a significantly positive linear relationship between the CCC measure and county-level per capita Medicare spending. This area-level measure can be operationalized to identify counties that might benefit from targeted efforts designed to optimally manage and prevent chronic illness.

### Keywords

GIS; health care spending; multiple chronic conditions; multimorbidity

## Introduction

Chronic health conditions can have a long-lasting clinical course that worsens over time if left untreated, and their risk factors (eg, tobacco, alcohol, inactivity, diet) are the leading causes of preventable deaths in the United States and the world.[1] People diagnosed with multiple chronic conditions (MCC) have a diagnosis of ≥2 concurrent chronic conditions.[2] Approximately 25% of US adults have MCC.[3] In 2017, of the 33.7 million Medicare Fee-for-Service (FFS) beneficiaries[4] aged ≥65 years, 67.6% were diagnosed with MCC.[5]

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At the individual level, having MCC is associated with higher risk of mortality,[6] lower quality of life,[7] and higher per capita Medicare spending[8,9] than people with ≤2 chronic conditions. MCC is a marker for medical complexity[9–11] and is associated with a majority of health care costs in the United States.[12] Recent increases in per capita Medicare spending correspond to an increase in MCC prevalence.[13]

An important step toward reducing per capita costs of health care is to improve the health of populations by identifying geographic areas that bear a disproportionately high burden of unfavorable chronic health conditions.[14,15] The genesis of this study was based on the observation that the geographic pattern of county-level MCC prevalence among Medicare FFS beneficiaries[12] was dissimilar from the geographic pattern of per capita spending for this cohort.[12] This low correlation suggests that the way in which the Centers for Medicare & Medicaid Services (CMS) measured county-level prevalence of MCC did not fully capture the medical complexity of the beneficiaries.

Quantifying the geographic variation of chronic disease prevalence has focused on single chronic illnesses such as diabetes,[16] cancer,[17,18] chronic obstructive pulmonary disease (COPD),[19] and others. Currently, there is no ecologic measure of the collective burden of common chronic conditions borne by a population, but one promising approach would be based on the Hierarchical Condition Categories (HCC) model developed by CMS.[10,11] However, HCC was not developed to produce a county-level measure of disease burden based on a collection of chronic conditions.

This study quantified the collective burden of MCC at the population level using a publicly-available county-level data set representing all Medicare FFS beneficiaries of any age. This new composite measure of chronic disease burden is called the concentration of chronic conditions (CCC). The geographic patterns of this measure were positively associated with per capita health care spending and that association varied across geographic space. This suggests that improving the health of populations in counties with higher than expected levels of spending relative to their disease burden could reduce the total costs associated with chronic disease care in a county, and subsequently in the United States as a whole.

## Methods

CMS published county-level data about the number of Medicare beneficiaries enrolled in Medicare Parts A and B, Medicare Part A only, or Medicare Part B only. Data on total Medicare FFS payments in 2017 for all Medicare services covered were included.[4] This study was limited to Medicare FFS beneficiaries because data about chronic disease or spending among Medicare Advantage beneficiaries were not publicly available. CMS publishes chronic conditions data for all ages, ages <65 years, and ages ≥65 years, but this study used all ages because county-level spending data published by CMS included beneficiaries of all ages. All FFS beneficiaries residing in the 50 states or the District of Columbia were included in the analyses.

CMS publishes precomputed chronic disease data for this cohort at the county level. Data included county-level prevalence estimates for 21 selected chronic conditions.[20]

CMS defined each chronic condition as the presence of any disease-specific *International Classification of Diseases, 10th Revision, Clinical Modification* diagnosis codes on a Medicare claim. Only 16 of the 21 conditions were included in this analysis because the prevalence of alcohol abuse (1.8%), drug abuse (1.7%), hepatitis (0.8%), HIV/AIDS (0.4%), or autism (0.2%) was very low.

Conditions used for this analysis include Alzheimer's disease and related dementia, arthritis, asthma, atrial fibrillation, cancer, chronic kidney disease, COPD, depression, diabetes, heart failure, hyperlipidemia, hypertension, ischemic heart disease, osteoporosis, schizophrenia, and stroke. County-level prevalence of each chronic condition is expressed as a percent using the count of beneficiaries with the condition as the numerator and the count of FFS beneficiaries as the denominator.

Per capita FFS Medicare spending in each county was calculated using the total Medicare spending among FFS beneficiaries as the numerator and all FFS beneficiaries as the denominator. Spending data were standardized to account for variations in Medicare spending for the same service in different geographical areas, but did not account for differences in individual health status.[21] The data only capture the portion paid by FFS Medicare; they do not include any out-of-pocket payments from patients or Medicare Advantage payments.

Some conditions were highly prevalent and some were rare,[22] but the national-level prevalence among the array of 16 selected conditions and the county-level prevalence of each specific condition both showed wide variation (Table 1). CCC addresses this problem by scoring each county according to the number of chronic conditions in the county that were in the highest or lowest decile of all counties in the United States. Using deciles of county-level prevalence for each selected condition ensured that the prevalence of all conditions was scaled to the same numerical domain.

The prevalence of some conditions had to be estimated because CMS suppresses condition-specific data for counties with <10 diagnosed beneficiaries. However, excluding these counties[23] presents a rural bias given that these populations have the highest prevalence of unhealthy behaviors that lead to many of these chronic conditions.[24] To address the issue of counties with suppressed data, the research team imputed the county-level number of beneficiaries with a given condition. This was done by subtracting the number of observed beneficiaries with the condition in non-suppressed counties from the observed number of beneficiaries with the condition in the state. Then, the difference was distributed to the suppressed counties based on their proportion of the total number beneficiaries in the state.

After imputing beneficiaries, the research team then needed to address the problem of rate reliability. The National Center for Health Statistics (NCHS) considers a mortality rate as reliable if it is based on at least 20 individuals.[25] To address the difficulty in obtaining reliable rates in counties with fewer than 20 cases for a given condition, the team borrowed the observed and imputed cases from neighboring counties until there were enough cases to calculate a reliable estimate. This approach has been used elsewhere.[25] To borrow these data, the team generated a neighborhood matrix based on "as-the-crow-flies" distances from the population-weighted centroids of each county to the population-weighted centroids of all other counties in the United States. Then, for a given county, the team only used the set of neighboring counties needed to obtain 20 beneficiaries.

In all, 10.8% (n = 340) of counties in the United States had to borrow data from at least 1 neighbor; of those, 261 counties borrowed exactly 1 neighbor, 60 counties borrowed exactly 2 neighbors, and 19 counties borrowed ≥3 neighbors. For a given county, the condition that needed to borrow the largest number of neighboring counties defined the set of neighboring counties used to calculate the prevalence estimate for all counties, even when the other conditions had more than 20 beneficiaries.

Then, the research team aggregated the county-level (1) total number of beneficiaries, (2) observed or imputed number of beneficiaries with a condition, and (3) total spending in the set of counties. After performing these procedures, the team recalculated the prevalence for each condition by dividing the county-level number of beneficiaries with a condition by the number of FFS beneficiaries in the county.

For a given county, each condition received a score of 1, 0, or −1 depending on its prevalence relative to the prevalence among all 3142 counties in the United States. A value of 1 indicated that a given condition was highly prevalent and in the upper decile (≥90%) of all counties. A value of −1 indicated that the prevalence of a given condition was low and in the lower decile (≤10%). All other counties were assigned a score of zero for that given condition. The CCC for a county is the net value of the of the sum of the scores. In this case, there were 16 conditions, thus the CCC values can take one of 33 discrete values ranging from −16 to 16. A negative value indicates a low burden of chronic conditions and a positive value indicates a high burden of chronic conditions.

Seven categories were created to map CCC. Counties with a moderate concentration of multiple chronic conditions (CCC = 0) were symbolized as light gray. The remaining 6 classes were symbolized using a diverging color scheme consisting of reds and blues; the color intensity increases as CCC values diverge from zero. Counties with high concentration values (CCC >0) were subdivided into 3 categories (1 to 3, 4 to 8, and 9 to 16) and symbolized in red to communicate that these counties have the highest burden of these chronic conditions. Counties with low concentration values (CCC <0) were subdivided into 3 categories (−1 to −3, −4 to −8, and −9 to −16) and symbolized in blue to communicate that these counties have the lowest burden of these chronic conditions.

Pearson *R* correlation was conducted to test the association of county-level CCC with county-level per capita spending among FFS beneficiaries across the United States. The research team then tested whether the association differed by urban-rural status using the NCHS 2013 Urban-Rural Classification System for Counties.[26] This classification system uses 2010 Census data to assign each county in the United States to one of 6 urban-rural classes (4 metropolitan, 1 micropolitan, and 1 noncore/rural).

Finally, ordinary least squares (OLS) regression was used to quantify county-level per capita spending as a function of the burden of disease as measured using CCC.[26] Then residual values of that OLS regression model were mapped in dollars to show where the per capita spending is significantly higher or lower than what would be expected given the county-level CCC measure. Counties symbolized in the most intense red or blue colors have per capita spending residuals >2 deviations from the mean.

## Results

There were 54,577,161 Medicare FFS beneficiaries of any age and approximately $347.9 billion in Medicare spending (or $6359 per FFS beneficiary) in 2017. The most prevalent chronic condition was hypertension (55.0%, or an estimated 30.0 million beneficiaries) and the least prevalent was schizophrenia (Table 1). Across all 3142 counties, there was a positive linear relationship between the burden of chronic conditions measured using the county-level CCC and per capita Medicare FFS spending ($r = 0.648$, $P < 0.001$). The association between CCC and per capita spending remained significant when stratified by NCHS metropolitan classes: large central and fringe metropolitan ($r = 0.6756$, $P < 0.001$); medium and small metropolitan ($r = 0.6532$, $P < 0.001$); and micropolitan and noncore (nonmetropolitan) ($r = 0.6419$, $P < 0.001$). Counties with a high burden of chronic disease (CCC ≥9) had per capita spending ($12,767) that was nearly twice as high as per capita spending in counties with the lowest burden of chronic disease ($7004) (Table 2).

On the map of the CCC measure for US counties (Figure 1), 19.6% of FFS Medicare beneficiaries resided in one of the 31.2% of counties with a low burden of chronic disease (symbolized as blue). These regions include counties in the Pacific Northwest, Wyoming, Utah, Colorado, the upper Midwest, and portions of New England and the Mid-Atlantic states. Conversely, 47.6% of the FFS Medicare beneficiaries resided in one of the 34.6% of the counties with high burdens of chronic disease (symbolized as red). These counties were found in the southern and eastern US. The counties with the highest CCC burden were in southern Ohio, eastern Kentucky, eastern Michigan, and much of the eastern seaboard from Massachusetts through North Carolina. North central Pennsylvania and western New York, the Mississippi valley, and the southern plains (Kansas, Oklahoma, and Texas) also had high CCC measures.

The geographic distribution of per capita Medicare spending (Figure 2A) shows that most counties in Kansas, Oklahoma, Texas, Louisiana, Mississippi, Alabama, Georgia, and Florida had relatively high levels of spending. Except for southern California, the lowest levels of spending were in the western states (Washington, Idaho, Montana, Oregon, Wyoming, California, Nevada, Colorado, New Mexico, and Arizona) and in the northeastern states (New York, Maine, Vermont, New Hampshire, western Massachusetts, and eastern Connecticut). Counties that have higher than expected levels of per capita spending given the county’s CCC are shaded in the most intense reds (Figure 2B). Per capita spending in these counties could potentially be reduced if their level of chronic disease burden were reduced.

## Discussion

This work presents a novel measure of chronic disease burden in the United States called the concentration of chronic conditions (CCC). It was created because currently there is no ecologic measure of the collective burden of common chronic conditions borne by a population. This county-level measure of chronic disease burden was significantly associated with county-level per capita Medicare spending. These results can potentially be used to identify counties to target for population-level efforts focused on the prevention and management of chronic diseases. This will potentially result in Medicare spending reductions.

Curbing costs is important given the significant levels of spending that are not accounted for in this study. First, chronic disease prevalence or spending data were only available for beneficiaries enrolled in Medicare FFS programs. The implication is that one can expect current aggregate Medicare spending to be much higher than what is reported herein simply because the aggregated FFS data were missing 34% of beneficiaries enrolled in Medicare Advantage programs.[27] Second, this study does not account for the baby boom generation,[28] who are continually being added to the Medicare-eligible population. Aggregate spending for this group will naturally increase over time in proportion to the growth of the Medicare-eligible population. Although the exact levels of spending for the Medicare Advantage or baby boomer populations are not known, it is reasonable to expect that they will experience some health benefits in counties where effective chronic disease interventions are implemented.

Population-level prevention and management of these chronic conditions could start by addressing behavioral risk factors,[24] social determinants,[29] and levels of health care access that local populations may share.[30] Prevalence of conditions with common risk factors could potentially be reduced by addressing contextual risk factors (eg, area-level poverty, access to health care, environmental exposures) or individual behavior (eg, smoking, physical activity, nutrition). Population-level public health interventions and health system factors may influence risk and severity of several conditions at once if there are effective programs in place to reduce these risks. For example, implementation of an effective smoking prevention program in a county could have a measurable impact on the prevalence of coronary heart disease,[31] COPD,[32] cancer,[33] and stroke.[34]

Another way to decrease the burden of chronic disease is through increased access to primary care. High-performing primary care systems are associated with reduced health care costs and lower morbidity and mortality related to chronic disease.[35] High-quality primary care encompasses primary, secondary, and tertiary prevention of chronic disease as well as effective chronic disease management and care for patients with multiple chronic conditions. Thus, one potential intervention to effectively manage and prevent chronic conditions is to improve access to primary care.[2,36,37]

One strength of the CCC measure is that it provides a way to show the geographic distribution of chronic condition burden despite the unique statistical distributions of the 16 chronic conditions; the range of county-level estimates for the most prevalent condition (hypertension) was an order of magnitude larger than the condition with the least prevalent (schizophrenia) (Table 1).

Another strength is that the prevalence estimate for each county has the same minimum level of statistically reliability achieved by borrowing chronic condition data from its neighboring counties. This is particularly important for rural counties that have poorer health outcomes[24] but that often are excluded from county-level analyses because of inadequate methods to address data suppression.[23] Finally, the CCC method assured that a county only borrowed data from the same urban-rural class to reduce the possibility that the health characteristics of a rural county were obscured by those of urban counties.

Future researchers may be interested in understanding how local social determinants of health, health care system performance and management, and state or national policy shaped the relationship between the CCC and Medicare spending observed in this study. County-level socioeconomic factors such as poverty, educational attainment, and marital status also may explain why per capita spending was higher or lower than expected given the level of chronic disease burden. Conversely, focused inquiry into these counties with a high burden of chronic disease but lower than expected costs might yield knowledge that could be translated to other areas with high chronic disease burden and high costs. Future researchers could examine which factors in these counties led to decreased spending to prepare case studies for use by other counties with higher levels of spending.

This study demonstrates the kinds of analyses that can be conducted using aggregated data for the purpose of identifying counties with high chronic disease burden. The research team used publicly-available CMS data aggregated at the county level, which were the best data available to the team at the time. However, claim- or beneficiary-level data would enable the production of more geographically detailed CCC and spending measures. Furthermore, this data would address several limitation of this study such as the need to impute the number of beneficiaries with a chronic condition in counties with suppressed data. Individual-level data could help identify which conditions have the highest costs and identify the most prevalent combinations of chronic conditions in a county, which is important because some chronic conditions are more costly than others.[13,38] Applying weights based on severity may help explain the observed variability of Medicare spending in counties across the United States, but aggregated data prevented the team from disentangling the costs associated with conditions that are inexpensive to treat from those that are not. Relatedly, the team was unable to identify any individual-level spending amounts or adjust for individual-level spending outliers when using aggregated data. Furthermore, the team was unable to age-standardize prevalence estimates because the socioeconomic composition of beneficiaries was not available in the aggregated data. Publicly-available Medicare spending data are based on the data for all ages, which includes 8.6 million FFS beneficiaries aged <65 years. This could introduce a potential bias given that beneficiaries aged <65 years tend to be disabled and have a higher overall prevalence of chronic disease.[39,40] Finally, a potential geographic bias could have been introduced if beneficiaries who relocate to more comfortable climates during the hottest or coldest parts of the year obtain care while away from the residence noted in their CMS file.

One comprehensive way to address all of these limitations in future research is to use individual-level data to geographically disaggregate the HCC model into each of the 3142 counties in the United States. In the meantime, CCC can be leveraged to support interventions to improve population health and to reduce health care costs, and provides an important indicator of population health for multiple conditions simultaneously. Measuring county-level burden of chronic disease using CCC could lead to improvements in the health of populations in areas with the highest chronic disease burdens, which in turn could reduce the total costs associated with chronic disease care in the United States.

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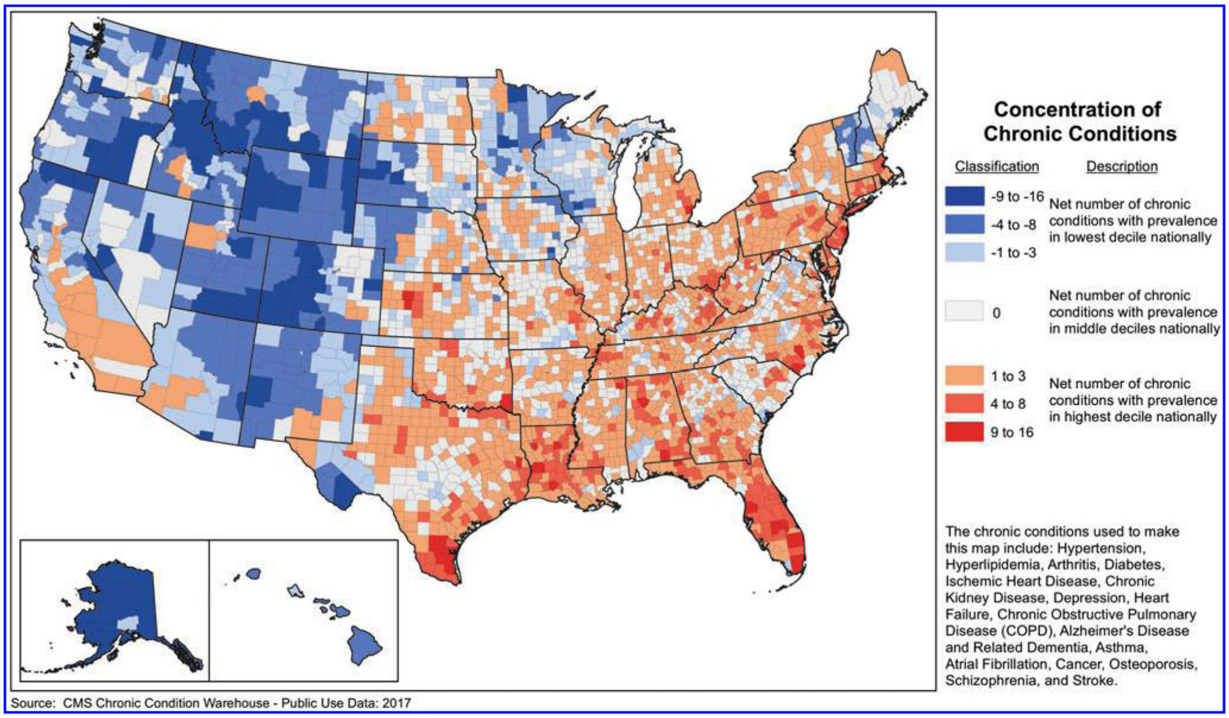


**FIG. 1.**

Concentration of chronic conditions in US counties among Medicare fee-for-service beneficiaries, 2017. The concentration of chronic conditions measure in a given county is the sum of the prevalence score for the following 16 conditions: hypertension, hyperlipidemia, arthritis, diabetes, ischemic heart disease, chronic kidney disease, depression, heart failure, chronic obstructive pulmonary disease, Alzheimer's disease and related dementia, asthma, atrial fibrillation, cancer, osteoporosis, schizophrenia, and stroke. For the given county, each chronic condition received a prevalence score of 1, 0, or −1 depending on the prevalence of each condition among all of the counties. A value of 1 indicates that the prevalence was in the upper decile among all counties and a value of −1 indicates that the prevalence was in the lower decile; a value of 0 indicates the prevalence in neither the upper nor lower decile.

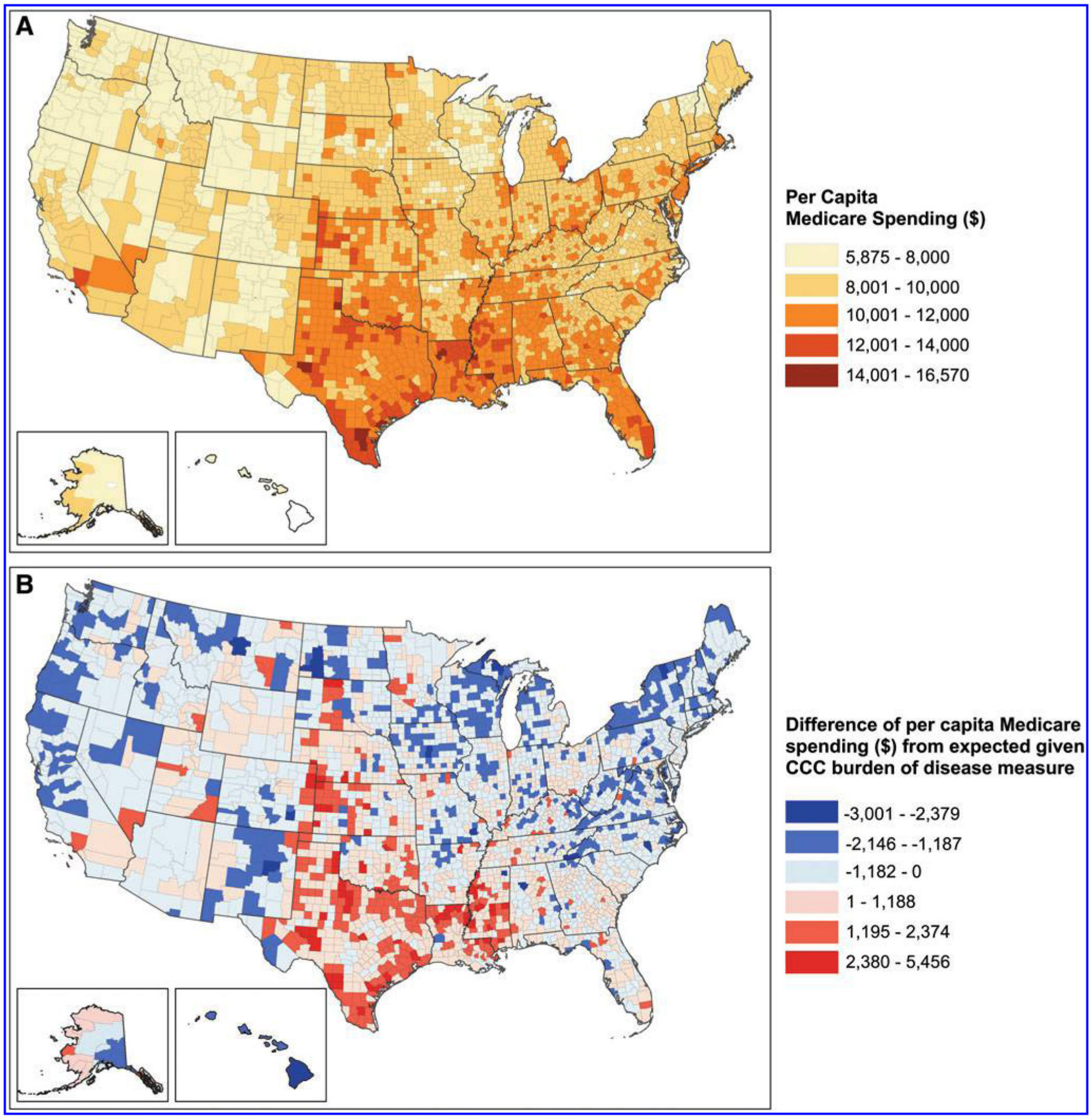


**FIG. 2.**
Per capita Medicare spending. **(A)** Per capita Medicare spending ($) among fee-for-service beneficiaries and **(B)** deviation of per capita spending ($) from expected given the concentration of chronic condition burden of disease measure, 2017.

## Table 1.

Prevalence of Selected Chronic Conditions Among Medicare Fee-for-Service Beneficiaries of All Ages in the 50 States and the District of Columbia, 2017

| Selected chronic condition | National-level prevalence (%) (n = 54,577,161) | County-level prevalence (%) (minimum, median, maximum) (n = 3142 counties) | Estimated number of FFS beneficiaries with selected chronic condition* (in millions) |
|---|---|---|---|
| 1. Hypertension | 55.0 | (28.8, 58.2, 74.9) | 30.0 |
| 2. Hyperlipidemia | 44.6 | (12.6, 39.3, 67.6) | 24.3 |
| 3. Arthritis | 30.0 | (18.2, 33.0, 57.2) | 16.3 |
| 4. Diabetes | 26.5 | (13.9, 26.6, 46.9) | 14.5 |
| 5. Ischemic Heart Disease | 26.5 | (8.2, 27.2, 49.6) | 14.5 |
| 6. Chronic Kidney Disease | 18.1 | (9.1, 22.9, 51.5) | 9.9 |
| 7. Depression | 16.7 | (5.2, 14.2, 28.0) | 9.1 |
| 8. Heart Failure | 13.5 | (5.7, 17.5, 35.9) | 7.4 |
| 9. Chronic Obstructive Pulmonary Disease | 11.2 | (4.7, 10.2, 25.0) | 6.1 |
| 10. Alzheimer's Disease and Related Dementia | 9.9 | (3.6, 12.4, 32.1) | 5.4 |
| 11. Asthma | 8.2 | (2.8, 8.1, 14.6) | 4.8 |
| 12. Atrial Fibrillation | 8.1 | (3.5, 7.4, 12.1) | 4.4 |
| 13. Cancer | 7.8 | (1.7, 4.3, 9.8) | 4.3 |
| 14. Osteoporosis | 6.0 | (1.2, 3.4, 9.5) | 3.3 |
| 15. Stroke | 4.0 | (1.4, 5.3, 14) | 2.2 |
| 16. Schizophrenia | 3.7 | (0.5, 2.5, 17.5) | 2.0 |

[*] These condition categories are not mutually exclusive because beneficiaries can have >1 condition.

FFS, fee-for-service.

**Table 2.**

Number of Counties and Medicare Fee-for-Service Beneficiaries and Per Capita Spending by Concentration of Chronic Conditions Classification and Metropolitan Status in US Counties, 2017

| | | | | Per capita FFS medicare spending ($) | | | |
|---|---|---|---|---|---|---|---|
| **Description** | **Map classification** | **Number of counties** | **Medicare FFS beneficiaries (%)** | **All counties (n = 3142)** | **Large (central/ fringe) metro counties (n = 436)** | **Medium/small metro counties (n = 730)** | **Non-metro counties (n = 1976)** |
| Net number of conditions in ≤10th percentile | −9 to −16 | 143 | 406,737 (1.2%) | 7004 | 6689 | 6647 | 7088 |
| | −4 to −8 | 283 | 2,010,452 (6.0%) | 7629 | 8100 | 7525 | 7500 |
| | −1 to −3 | 557 | 4,182,983 (12.4%) | 8553 | 8735 | 8335 | 8606 |
| Net number of conditions in >10th and <90th percentile | 0 | 1069 | 11,013,963 (32.8%) | 9610 | 9949 | 9344 | 9352 |
| Net number of conditions in ≥90th percentile | 1 to 3 | 774 | 10,057,704 (29.9) | 10,294 | 10,645 | 9910 | 10,082 |
| | 4 to 8 | 303 | 5,625,528 (16.7%) | 10,871 | 10,988 | 10,680 | 10,814 |
| | 9 to 16 | 13 | 320,894 (1.0%) | 12,767 | 12,920 | 12,152 | 11,910 |
| Total | | 3142 | 33,618,261 | 9774 | 10,275 | 9431 | 9282 |

FFS, fee-for-service.