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Research Article

Social Vulnerability and the Prevalence of Opioid Use Disorder Among Older Medicare Beneficiaries in U.S. Counties

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Abstract

Objectives: Recent research has investigated the factors associated with the prevalence of opioid use disorder (OUD) among older adults (65+), which has rapidly increased in the past decade. However, little is known about the relationship between social vulnerability and the prevalence of OUD, and even less is about whether the correlates of the prevalence of OUD vary across the social vulnerability spectrum. This study aims to fill these gaps.

Methods: We assemble a county-level data set in the contiguous United States (U.S.) by merging 2021 Medicare claims with the CDC's social vulnerability index and other covariates. Using the total number of older beneficiaries with OUD as the dependent variable and the total number of older beneficiaries as the offset, we implement a series of nested negative binomial regression models and then analyze by social vulnerability quartiles.

Results: Higher social vulnerability is associated with higher prevalence of OUD in U.S. counties. This association cannot be fully explained by the differences in the characteristics of older Medicare beneficiaries (e.g., average age) and/or other social conditions (e.g., social capital) across counties. Moreover, the group comparison tests indicate correlates of the prevalence of OUD vary across social vulnerability quartiles in that the average number of mental disorders is positively related to OUD prevalence in the least and the most vulnerable counties and social capital benefits the less vulnerable counties.

Discussion: A perspective drawing upon contextual factors, especially social vulnerability, may be more effective in reducing OUD among older adults in U.S. counties than a one-size-fits-all approach.

Keywords: Ecological study, Negative binomial regression, Social determinants of health, Substance use

Compared with other developed countries, the U.S. population has a relatively short life expectancy (Arias et al., 2021; Ho & Hendi, 2018). Between 2015 and 2017, life expectancy at birth declined slightly (Harper et al., 2021), a pattern not commonly observed in other peer countries (see Author Note 1); in fact, the gap with other countries has widened since 2020 (Andrasfay & Goldman, 2021). There are several explanations for the decline, such as increasing deaths of despair and stagnant cardiovascular mortality (Harper et al., 2021). Among these explanations, much attention has been given to opioid drug overdose (Case & Deaton, 2020) and the correlates of opioid-related deaths among middle-aged populations in U.S. counties (Monnat et al., 2019; Rigg et al., 2018). Nonetheless, Wilson and colleagues (2020) have reported that the opioid-related death rate increases more rapidly among older adults than other age groups, but little is known about the role of older adults (age ≥65) in the ongoing opioid epidemic (Huhn et al., 2018). As the U.S. population is aging rapidly and the baby boomers, who lived through an era when drug use was more socially acceptable, are entering older adulthood (Carr, 2023), it is critical to understand how older adults may shape the development of the opioid epidemic in the future.

Between 2013 and 2018, the prevalence of opioid use disorder (OUD) among older Medicare beneficiaries has increased from 4.6 OUD cases per 1,000 beneficiaries to almost 16 (per 1,000 beneficiaries), and the increasing pattern is observed regardless of race/ethnicity, gender, and socioeconomic status (Shoff et al., 2021). Opioid use disorder strongly predicts fatal drug overdose and other comorbidities (Strang et al., 2020). In 2019, it was estimated that OUD-attributable Medicare spending among older beneficiaries was $2.9 billion, which

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was more than 60% higher than the spending among younger beneficiaries (Mark et al., 2023).

There are several reasons why older adults are uniquely vulnerable to OUD. First, the inevitable aging process makes older adults more likely to experience physical pain and mental illness than younger individuals (Le et al., 2016; Maree et al., 2016). Hence, health care providers may prescribe opioids to manage older adults' health conditions. Given that prescription opioids are related to the onset of OUD (Butler et al., 2016), older adults may face a heightened risk of OUD. Second, the life-course events in older adulthood, such as retirement and bereavement, may be associated with the loss of social roles and a sense of isolation, which increases the risk of having mental health conditions and the development of OUD (Cochran et al., 2017; Huhn et al., 2018; Maree et al., 2016). Finally, due to the fear of stigma and relatively low awareness of OUD (Le Roux et al., 2016; Wang & Andrade, 2013), older adults may overlook OUD symptoms and have severe health consequences.

To explore the factors underlying the increasing trend in OUD among older adults, several scholars have found that high county-level social isolation is associated with not only a heightened individual-level risk of OUD (Yang et al., 2022c), but also a higher prevalence of OUD at the county-level (Yang et al., 2022b). In addition, residential stability is negatively related to the prevalence of OUD in U.S. counties, especially metropolitan counties (Yang et al., 2022b). Using newly developed spatial analysis techniques, a study suggests that the correlates of the county-level prevalence of OUD may vary across space and the characteristics of beneficiaries, such as the average mental health conditions and the average financial burden, may outweigh the social conditions of a county (Yang et al., 2022a). Despite recent effort, little research has focused on the relationship between social vulnerability and prevalence of OUD among older adults.

At the aggregate level, the U.S. Centers for Diseases Control and Prevention (CDC) have developed the social vulnerability index (SVI) to assess the variation of social factors that are related to social inequality and shape susceptibility to both natural and man-made emergencies and ability to manage the stress caused by the emergencies (Centers for Disease Control and Prevention, 2022). In the U.S., social vulnerability has been found to adversely affect various health outcomes, such as cancer and cardiovascular disease mortality (Ganatra et al., 2022), teenage pregnancy (Yee et al., 2019), COVID-19 infection (Dasgupta et al., 2020), and preventive health behavior among older adults (Strully & Yang, 2022). Other developed or rapidly aging societies have also reported positive associations between social vulnerability and cause-specific mortality (Barbi et al., 2018), risk of natural hazards (Maharani & Lee, 2017), and food insecurity (Ware et al., 2021).

Prior research has paid little attention to the relationship between social vulnerability and prevalence of OUD. This study argues that more socially vulnerable communities are subject to a higher prevalence of OUD and the correlates of the prevalence of OUD may vary by levels of social vulnerability for the following reasons. First, social vulnerability reflects various susceptibilities at the community level, such as concentrations of marginalized or disadvantaged populations and substandard infrastructure. According to the socioecological model (Bronfenbrenner, 1986), individual health outcomes or behavior are shaped by various systems and community context has been identified as an important system. As such, social vulnerability can go beyond emergency preparedness and be applied to slowly emerging public health concerns (Gay et al., 2016), such as the prevalence of OUD. Second, the commonly used indicators of social vulnerability, such as housing and transportation, are directly related to critical health theories, such as fundamental cause theory (Phelan et al., 2010), the health belief model (Maiman & Becker, 1974), and the collective efficacy model (Sampson et al., 1997). For example, fundamental cause theory asserts that substandard socioeconomic conditions undermine the vitality of local opportunity structures and lower investment in infrastructure (e.g., public transportation), which can undermine both individual and population health (i.e., aggregate place-based health). Older adults exposed to such an environment may have limited access to health care or insufficient information about drug misuse and the prevalence of OUD may increase accordingly. Furthermore, the health belief model suggests that living in areas with high concentrations of population with disability or households without a vehicle may alter one's perceived susceptibility or barriers to health care. These factors may elevate older adults' daily stress or aggravate their mental health burden, which are associated with a heightened risk of OUD (Cochran et al., 2017; Huhn et al., 2018; Maree et al., 2016). Third, recent literature has suggested that population health outcomes tend to be place-specific and demonstrate distinctive spatial patterns (Brazil, 2022; Yang et al., 2022a). The correlates underlying these patterns are likely to differ across geography (Keyes et al., 2014) and social vulnerability (Strully & Yang, 2022). Nonetheless, prior research has not examined whether the correlates of county-level prevalence of OUD vary by social vulnerability.

Drawing upon the discussion above, this study aims to advance the extant literature by (1) investigating the correlates of the prevalence of OUD, a strong predictor of opioid-related deaths (Strang et al., 2020), in U.S. counties with the latest Medicare data, (2) exploring whether and how county-level social vulnerability is related to the prevalence of OUD, and (3) examining whether there is any difference in the correlates of prevalence of OUD across the social vulnerability spectrum. Counties are an appropriate unit of analysis due to their policy and administration relevance in the U.S. and they have been commonly used to explore geographic inequalities in demographic or health outcomes (Hugo, 2017; Lobao et al., 2007).

Data and Methods

Several nationwide data sources focusing on counties in the contiguous U.S. ($N = 3{,}103$) are combined to form the analytical data set. Although counties with missing values were excluded ($N = 5$), the final data set covers more than 99% of the population (see Author Note 2). The counts of older Medicare beneficiaries with OUD are from the Centers for Medicare & Medicaid Services (CMS), and the aggregate characteristics of beneficiaries are based on the following three 2021 beneficiary-level data files from CMS: (1) the Medicare Beneficiary Summary File (MBSF) Base segment, (2) MBSF Chronic Conditions segment, and (3) MBSF Other Chronic and Potentially Disabling Conditions Segment. To be included in this study, beneficiaries must meet the following criteria: aged 65 or older and continuously enrolled in Medicare Fee-for-Service Parts A, B, and D for all 12 months of the 2021 calendar year and all 12 months of 2020. It is necessary to consider continuous enrollment for 2020 because the OUD status is determined with a one-year lookback period (see below for detail). Beneficiary-level characteristics, such as age and race/ethnicity, are aggregated to the county level. The 2017–2021 American Community Survey (ACS) 5-year estimates (U.S. Census Bureau, 2022) are the primary source for other county-level measures.

The dependent variable is the *count of older Medicare beneficiaries with OUD,* and the total number of eligible older Medicare beneficiaries in a county is included in the analysis as an exposure variable. Doing so allows us to interpret the dependent variable as the *OUD incidence rate* in a county. A beneficiary's OUD status is determined with the OUD flag drawn from three opioid-related subindicators: (1) diagnosis and procedure basis for OUD, (2) opioid-related hospitalization or emergency department visits, and (3) use of medication-assisted treatment (Research Data Assistance Center, 2022). When a beneficiary has any of the three subindicators, s/he is defined as a beneficiary with OUD.

The overall *SVI* is a composite score based on the following four themes: (1) "Socioeconomic Status theme" includes poverty, unemployment rate, income per capita, and percentage of the population aged 25 and older without a high school diploma. (2) "Household Composition and Disability theme" considers the percentage of the population aged 65 or older, the percentage of the population aged 17 or younger, the percentage of the civilian population with a disability, and the percentage of single-parent households with children under 18. (3) "Minority Status and Language theme" consists of the percentage of the minority population and the percentage of the population aged 5 and older who speak English "less than well." (4) "Housing Type and Transportation theme" comprises the percentage of housing structures with 10 or more units, the percentage of mobile homes, the percentage of occupied housing units with more people than rooms, the percentage of households without a vehicle, and percentage of the population in group quarters. Among these SVI variables, many (e.g., poverty and income) are classified as the socioeconomic conditions critical to the fundamental cause theory (Phelan et al., 2010), and lack of transportation, limited language ability, or crowded housing units reflect perceived barriers to health care and perceived susceptibility to diseases, which may in turn increase the risk of OUD as both the health belief and socioecological models suggest (Bronfenbrenner, 1986; Maiman & Becker, 1974).

Following the ranking method used by CDC, we first create percentile ranking values from 0 to 1 for each variable, with higher values indicating greater vulnerability. We then sum the percentiles for the variables of each theme and generate theme-specific percentile rankings. Finally, we sum the theme-specific percentiles to obtain the overall percentiles and create the percentile rankings based on the overall percentiles (Centers for Disease Control and Prevention, 2022; see Author Note 3). Instead of using the percentiles directly, we create four quartiles for the analysis to understand the potential nonlinear relationship between SVI and OUD incidence rates.

We create four measures to assess a county's social conditions: The *social isolation index* (among older adults), *age segregation* (see Author Note 4), *residential stability*, and *social capital*. The social isolation index is a principal component analysis (PCA) score drawn from the following four variables: Percentage of older adults with a disability; percentage of older adults who were divorced, separated, or widowed; percentage of older adults having difficulty living independently; and percentage of older adults living in poverty. Each variable has a factor loading higher than 0.65, and a single factor can reflect more than 60% of the total variation among these variables. This social isolation index was designed by the United Health Foundation (2018) and has been recently used in opioid-related research (Yang et al., 2022b). As for age segregation, we apply the exposure dimension of segregation (Massey & Denton, 1988) to two age groups: Older (≥65) and younger (<65) populations. The age segregation gauges the extent to which older adults are exposed only to one another. Higher values suggest higher levels of age segregation in that older adults tend to live close to other older adults rather than younger populations. This indicator is based on Bell's segregation measure (Bell, 1954). *Residential stability* refers to the average of two standardized variables: The percentage of owner-occupied housing units and the percentage of households living in the same housing unit for at least 5 years. Finally, based on Putnam's work (1994), Rupasingha and colleagues (2006) have developed a social capital index. This index is a PCA score of the following four variables: Density of establishments in civic, social, and recreational organizations (per 1,000 population), presidential voter turnout, census response rate, and the number of nonprofit organizations. Social capital assesses the potential connections and social networks among residents and captures the norm of reciprocity and trustworthiness from these connections (Rupasingha et al., 2006; see Author Note 5).

The following variables are created regarding the characteristics of Medicare beneficiaries in a county. The *average age of a county's beneficiaries (in years)* is obtained. Centers for Medicare & Medicaid Services calculate the hierarchical condition category (HCC) score for each beneficiary, which assesses his/her potential Medicare cost. The HCC score is normalized to 1, and beneficiaries with a score that is less than 1 impose a lighter financial burden on Medicare than those with a score greater than 1 (Hoffman et al., 2018). The *average HCC score* is calculated. The *average number of mental health conditions* is the mean value of beneficiaries' mental health conditions, including anxiety disorders, depressive disorders, bipolar disorder, and schizophrenia and other psychotic disorders. The *average number of physical conditions* refers to the mean value of beneficiaries' physical conditions, including chronic obstructive pulmonary disease, diabetes, chronic kidney disease, and hypertension. The *percentage of female beneficiaries* is calculated by dividing the total number of female beneficiaries by the total number of beneficiaries. *Percentage of non-Hispanic white beneficiaries*, *percentage of non-Hispanic Black beneficiaries*, and *percentage of Hispanic beneficiaries* are measured by dividing the number of beneficiaries in each racial/ethnic group by the total number of beneficiaries. Dual-eligibility status (i.e., eligible for both Medicare and Medicaid) is a proxy for a beneficiary's socioeconomic status, and we divide the total number of dually eligible beneficiaries by the total number of beneficiaries to obtain the *percentage of dually eligible beneficiaries*.

We use negative binomial regression to analyze the county-level data as the dependent variable is overdispersed (Agresti, 2012). The analytic strategy is divided into three phases. We first obtain the descriptive statistics of variables for all counties and by SVI quartile and conduct pairwise *t* tests to understand if there is any difference across quartiles in the mean values of these variables. The second phase focuses on four nested models. Model 1 only considers the SVI quartiles. Social isolation index and age segregation are added to Model 2, and the characteristics of beneficiaries are added to Model 3. The final model (Model 4) considers residential stability and social capital. The nested models allow us to understand how the associations between SVI quartiles and OUD incidence rates may change with different sets of variables. In the last phase, we implement the full model by SVI quartiles to investigate whether the correlates of OUD incidence rates vary by quartiles.

Results

Table 1 presents the descriptive statistics of variables for all counties and by SVI quartiles, and the last column includes the pairwise group comparison test results. Several findings are noteworthy. First, the number of older beneficiaries with OUD varies greatly across SVI groups, increasing with social vulnerability. Counties in the most vulnerable group (i.e., fourth quartile or Q4), on average, have more than 100 beneficiaries with OUD (100.52), which is 2.4 times higher than counties in the least vulnerable group (41.89). The differences in the number of beneficiaries with OUD between the least vulnerable group and other groups are statistically significant. Second, the isolation index also increases with social vulnerability in that the average isolation index is −0.76 in the least vulnerable group and elevates to 0.76 in the most vulnerable group. The differences across SVI groups are statistically significant. Regarding age segregation, although the mean values do not seem to vary greatly, the most vulnerable group has the lowest age segregation score compared with other groups, which is supported by the pairwise test results.

Third, residential stability and social capital are stronger in counties with low social vulnerability than those with high social vulnerability. For example, residential stability is 0.42 in the least vulnerable group and −0.37 in the most vulnerable group. These relationships indicate that residential stability and social capital are negatively associated with social vulnerability, and these variables' group differences are all statistically significant. Fourth, there are apparent differences in the characteristics of older beneficiaries across the social vulnerability groups. For example, older beneficiaries living in counties in the least vulnerable group impose the lowest burden on the health care system (HCC = 0.95) compared to their counterparts in more vulnerable groups. They also have the fewest mental (0.35) and physical (1.2) conditions and the lowest percentage of dually eligible beneficiaries (8.91) compared with older beneficiaries in counties of the second, third, and fourth SVI quartiles.

We visualize the prevalence of OUD among older Medicare beneficiaries and the SVI quartiles in Figures 1 and 2. High levels of OUD prevalence are clustered in the Pacific Coast, Mountain States (e.g., Nevada, Idaho, and Utah), Oklahoma, Eastern Texas, the Black Belt, and Appalachia Region. Regarding SVI, counties in the South, the US/Mexico border, and the Pacific Coast are more likely

Table 1. Descriptive Statistics of All Variables and Comparisons Between Groups

Variables	Total (N = 3,103)		Q1 (n = 777)		Q2 (n = 775)		Q3 (n = 775)		Q4 (n = 776)		Group comparison*
	Mean	*SD*	Mean	*SD*	Mean	*SD*	Mean	*SD*	Mean	*SD*	
OUD beneficiaries	79.67	(203.04)	41.89	(93.53)	78.93	(159.89)	97.42	(222.81)	100.52	(280.99)	a, b, c
Social isolation index	0.00	(1.00)	−0.76	(0.84)	−0.22	(0.77)	0.22	(0.84)	0.76	(0.87)	a, b, c, d, e, f
Age segregation	0.21	(0.05)	0.22	(0.05)	0.21	(0.05)	0.21	(0.05)	0.20	(0.04)	b, c, e, f
Average age of beneficiaries	75.86	(0.74)	75.87	(0.85)	75.82	(0.70)	75.80	(0.72)	75.94	(0.65)	e, f
Average HCC score	1.02	(0.12)	0.95	(0.09)	1.00	(0.09)	1.04	(0.15)	1.09	(0.12)	a, b, c, d, e, f
Average number of mental disorders	0.39	(0.08)	0.35	(0.08)	0.39	(0.07)	0.41	(0.09)	0.41	(0.09)	a, b, c, d, e
Average number of physical conditions	1.33	(0.22)	1.20	(0.18)	1.29	(0.20)	1.37	(0.2)	1.46	(0.19)	a, b, c, d, e, f
% Female beneficiaries	57.81	(2.48)	57.11	(2.46)	57.62	(2.13)	58.06	(2.62)	58.44	(2.49)	a, b, c, d, e, f
% Non-Hispanic Blacks	4.54	(8.63)	0.84	(2.31)	2.00	(3.87)	3.97	(6.4)	11.36	(13.03)	a, b, c, d, e, f
% Hispanics	3.14	(8.68)	0.80	(1.65)	1.59	(3.28)	3.00	(6.87)	7.17	(14.73)	a, b, c, d, e, f
% Dual beneficiaries	14.72	(9.00)	8.91	(4.23)	12.47	(6.18)	16.06	(7.89)	21.46	(10.95)	a, b, c, d, e, f
Residential stability	0.01	(0.88)	0.42	(0.69)	0.08	(0.84)	−0.10	(0.89)	−0.37	(0.92)	a, b, c, d, e, f
Social capital	0.00	(1.00)	0.60	(1.12)	0.04	(0.91)	−0.24	(0.72)	−0.41	(0.88)	a, b, c, d, e, f

Notes: HCC = hierarchical condition category; OUD = opioid use disorder.
[*] *t* Tests were used to examine whether the mean values are statistically different between groups at the 95% confidence level.
"a" represents a significant difference between Q1 and Q2 groups.
"b" represents a significant difference between Q1 and Q3 groups.
"c" represents a significant difference between Q1 and Q4 groups.
"d" represents a significant difference between Q2 and Q3 groups.
"e" represents a significant difference between Q2 and Q4 groups.
"f" represents a significant difference between Q3 and Q4 groups.

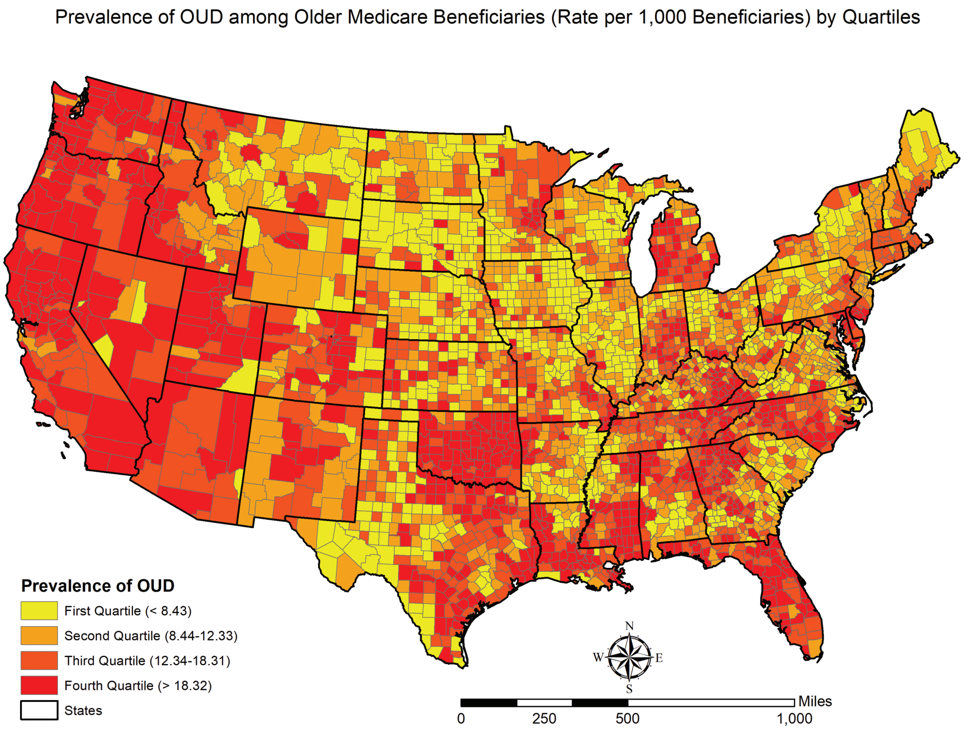

Figure 1. Map of the prevalence of opioid use disorder (OUD) among older Medicare beneficiaries (rate per 1,000 beneficiaries) by quartiles.

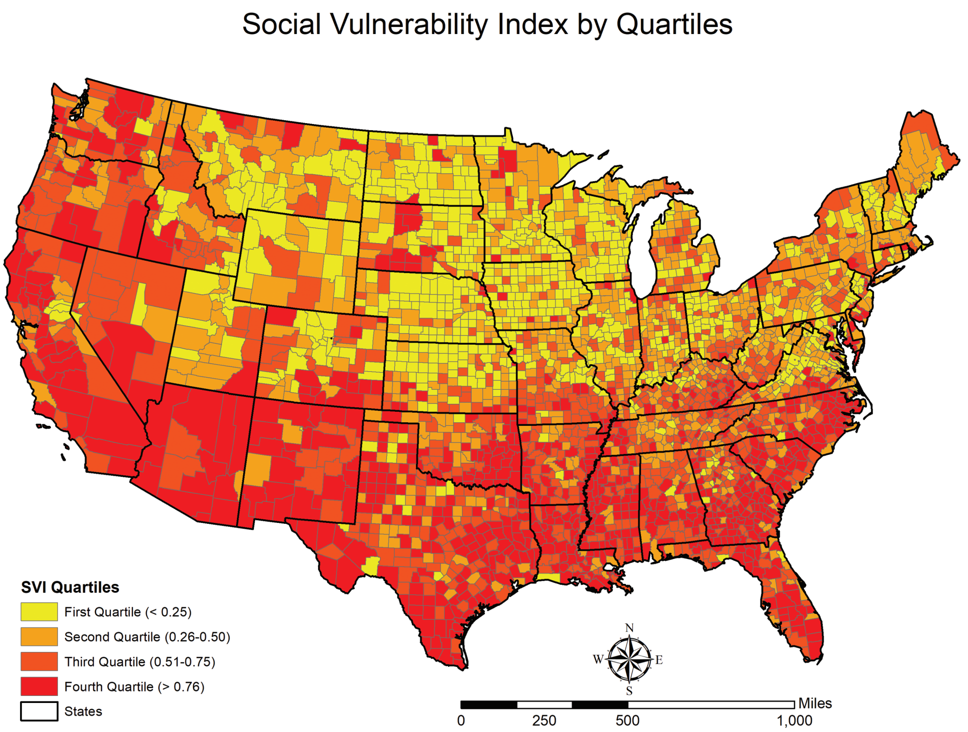

Figure 2. Map of social vulnerability index (SVI) by quartiles.

to have higher SVI values. The figures indicate a potential positive association between the prevalence of OUD and SVI.

The negative binomial regression results are summarized in Table 2. Following the analytic strategy, all counties are included in the analysis, and the SVI quartiles are used as a covariate. Model 1 only considers three dummy variables (using the least vulnerable group as the reference group), and the results suggest that higher levels of social vulnerability are associated with higher OUD incidence rates. Specifically, the OUD incidence rate in the second SVI quartile is 27% higher ((exp(0.240)−1) × 100% = 27.12%) than that in the least vulnerable quartile. The gap increases to 52% for the third quartile and 59% for the most vulnerable quartile.

Table 2. Negative Binomial Regression of Opioid Use Disorder Among Older Medicare Beneficiaries in U.S. Counties (N = 3,103)

Variables	Model 1	Model 2	Model 3	Model 4	VIF[a]
Social vulnerability index (Ref = Q1)					
Q2	0.240***	0.224***	0.163***	0.147***	1.70
	(0.028)	(0.028)	(0.027)	(0.027)	
Q3	0.418***	0.388***	0.303***	0.286***	2.10
	(0.028)	(0.030)	(0.029)	(0.030)	
Q4	0.465***	0.417***	0.368***	0.353***	3.10
	(0.028)	(0.033)	(0.035)	(0.037)	
Social isolation index		0.032*	0.014	0.012	1.83
		(0.013)	(0.013)	(0.013)	
Age segregation		−0.041	0.458*	0.652**	1.37
		(0.205)	(0.205)	(0.218)	
Average age of beneficiaries			−0.210***	−0.190***	1.66
			(0.016)	(0.017)	
Average HCC score			2.055***	1.965***	3.05
			(0.150)	(0.152)	
Average number of mental disorders			0.982***	0.905***	2.40
			(0.176)	(0.178)	
Average number of physical conditions			−0.549***	−0.584***	3.60
			(0.074)	(0.082)	
% Female beneficiaries			−0.006	−0.006	1.79
			(0.005)	(0.006)	
% Non-Hispanic Blacks			−0.007***	−0.007***	1.68
			(0.001)	(0.001)	
% Hispanics			−0.002	−0.003*	1.56
			(0.001)	(0.001)	
% Dual beneficiaries			0.001	0.001	1.96
			(0.001)	(0.001)	
Residential stability				−0.003	1.66
				(0.013)	
Social capital				−0.053***	1.71
				(0.012)	
Constant	−4.503***	−4.472***	9.991***	8.651***	—
	(0.020)	(0.046)	(1.099)	(1.141)	
Log of dispersion parameter	−1.459***	−1.461***	−1.673***	−1.683***	
	(0.031)	(0.031)	(0.032)	(0.031)	
Akaike Information Criterion	25,115.75	25,112.6	24,590.91	24,577.16	
Bayesian Information Criterion	25,145.96	25,154.88	24,681.52	24,679.85	

Notes: Standard errors in parentheses. HCC = hierarchical condition category.
[a]This column contains variance inflation factor (VIF) for the test of multicollinearity based on Model 4.
*p < .05. **p < .01. ***p < .001.

Including isolation index and age segregation (Model 2) partially accounts for the relationships between SVI quartiles and OUD incidence rates. For example, the coefficient estimate of the fourth quartile drops by 10% ((0.417–0.465)/0.465 × 100% = −10.32%) between Models 1 and 2. Similar changes are observed for other quartiles. In Model 3, the characteristics of beneficiaries further explain why SVI quartiles matter as the magnitude of the estimates reduces by 27% for the second quartile ((0.163–0.224)/0.224 × 100% = −27.23%), 22% for the third quartile ((0.303–0.388)/0.388 × 100% = −21.91%), and 12% for the fourth quartile ((0.368–0.417)/0.417 × 100% = −11.75%). Despite the reduction in coefficient estimates, all three quartiles still have higher OUD incidence rates than the least vulnerable group. In the final model, net of all covariates, the OUD incidence rate is approximately 16% ((exp(0.147)−1) × 100% = 15.84%) higher in the second quartile than in the first quartile. The difference in OUD incidence rate between the third and the first quartiles is widened to 33% ((exp(0.286)−1) × 100% = 33.11%). The largest gap is 42% ((exp(0.353)−1) × 100% = 42.33%) when comparing the most vulnerable group with the least vulnerable quartile.

Beyond the SVI quartiles, three critical findings are drawn from Table 2. First, social isolation is significant in Model 2, but it becomes statistically nonsignificant when the characteristics of beneficiaries and social capital are considered (Models 3 and 4). In contrast, the association between age segregation and OUD incidence rate seems to be suppressed by differences in demographic and health conditions of beneficiaries across counties. Specifically, high age segregation is not a significant factor for the OUD incidence rate in Model 2; however, in Models 3 and 4, higher levels of age segregation are associated with higher OUD incidence rates. For example, based on Model 4, increasing age segregation by 0.1 unit is related to a 7% increase in OUD incidence rates ((exp(0.652 × 0.1)−1) × 100% = 6.74%).

Second, residential stability is not related to OUD incidence rates, but social capital is beneficial to OUD prevalence. A one-unit increase in social capital is associated with a 5% decrease in OUD incidence rates ((1−exp(−0.053)) × 100% = 5.16%). Finally, the average HCC score (β = 1.965 in Model 4) and the average number of mental disorders (β = 0.905 in Model 4) are positively related to OUD incidence rates. Surprisingly, the average number of physical conditions is negatively associated with the prevalence of OUD (β = −0.584 in Model 4).

We implement the full model by SVI quartiles (models 5a–5d in Table 3) to better understand the potential differences in the correlates of OUD incidence rates across the spectrum of social vulnerability. We summarize the key findings as follows. First, the isolation index is not statistically significant across the four quartiles, but age segregation is positively associated with OUD incidence rates in the upper two quartiles. For counties in the third quartile, a 0.1 unit increase in age segregation is related to an almost 9% increase in OUD incidence rates ((exp(0.829 × 0.1)−1) × 100% = 8.64%). Counties in the most vulnerable quartile (Model 5d) are expected to experience an 18% increase in OUD prevalence, given the same change in age segregation. Coupled with the findings in Table 2, the adverse impact of age segregation on OUD incidence rates is mainly driven by socially vulnerable counties. However, the seemingly unrelated estimation (suest) test indicates that the group difference is not statistically significant.

Second, social capital reduces OUD incidence rates, but this beneficial effect is only observed for counties in the lowest two quartiles. For example, a one-unit increase in social capital is associated with a 5% decrease in OUD incidence rates for the least vulnerable group. Counties in the second quartile have a stronger relationship between social capital and OUD incidence rates because a one-unit increase in social capital is related to a 12% decrease in OUD incidence rates. The group difference is significant at the .1 level. Third,

Table 3. Negative Binomial Regression of Opioid Use Disorder Among Older Medicare Beneficiaries by Social Vulnerability Index

Variables	Model 5a (n = 777)	Model 5b (n = 775)	Model 5c (n = 775)	Model 5d (n = 776)	suest test[a]
Social isolation index	0.004	−0.008	0.010	0.045	2.06
	(0.025)	(0.026)	(0.026)	(0.025)	
Age segregation	0.066	0.649	0.829*	1.677***	5.02
	(0.474)	(0.416)	(0.412)	(0.492)	
Average age of beneficiaries	−0.071*	−0.182***	−0.201***	−0.289***	21.07***
	(0.028)	(0.033)	(0.036)	(0.038)	
Average HCC score	1.659***	1.878***	1.895***	2.427***	2.24
	(0.339)	(0.335)	(0.306)	(0.303)	
Average number of mental disorders	1.997***	0.526	0.184	1.148***	11.54**
	(0.384)	(0.394)	(0.360)	(0.321)	
Average number of physical conditions	−1.049***	−0.468**	−0.240	−0.641***	11.57**
	(0.160)	(0.161)	(0.162)	(0.183)	
% Female beneficiaries	−0.008	−0.008	−0.021	0.012	3.72
	(0.010)	(0.011)	(0.011)	(0.011)	
% Non-Hispanic Blacks	0.006	−0.006	−0.001	−0.012***	13.12**
	(0.006)	(0.005)	(0.003)	(0.002)	
% Hispanics	0.052***	0.021**	0.002	−0.005*	24.81***
	(0.014)	(0.007)	(0.004)	(0.002)	
% Dual beneficiaries	0.002	−0.006	0.006*	0.000	6.57+
	(0.004)	(0.003)	(0.003)	(0.003)	
Residential stability	0.031	0.001	−0.053*	0.028	5.38
	(0.030)	(0.028)	(0.026)	(0.024)	
Social capital	−0.051*	−0.126***	−0.029	−0.021	7.33+
	(0.023)	(0.029)	(0.034)	(0.023)	
Constant	0.184	8.338***	10.345***	14.796***	—
	(1.849)	(2.257)	(2.455)	(2.679)	
Log of dispersion parameter	−2.163***	−1.740***	−1.644***	−1.591***	—
	(0.081)	(0.064)	(0.061)	(0.062)	—

Notes: Standard errors in parentheses. HCC = hierarchical condition category.
[a]This column contains the suest (seemingly unrelated estimation) test results and significant findings indicate that there is a significant difference in a given variable across models 5a–5d.
+p < .10. *p < .05. **p < .01. ***p < .001.

higher average HCC scores are associated with higher OUD incidence rates. Although this association's magnitude seems to increase with social vulnerability, the suest test suggests that the difference between the most and least vulnerable groups is not statistically significant. Finally, the average number of mental disorders is positively related to OUD incidence rates in the least and the most vulnerable quartiles. Still, the average number of physical conditions demonstrates an opposite association with OUD except for the third quartile. These group differences are statistically significant for both variables.

Discussion and Conclusions

The results above allow us to revisit the goal of this study. We first aim to understand how the prevalence of OUD among older Medicare beneficiaries is correlated with contextual and social factors in U.S. counties. The results suggest that the characteristics of beneficiaries are associated with the OUD incidence rates. For example, older average ages are associated with a lower prevalence of OUD, which echoes some recent findings suggesting that old–old (age >70) beneficiaries are less likely to have OUD (Basu, 2020; Shoff et al., 2021) than young–old adults. Similarly, higher numbers of mental disorders are associated with a higher prevalence of OUD. One possible explanation is that older populations are more likely to receive prescription opioids when they have more mental disorders (Do, 2020). As such, when older beneficiaries are exposed to more prescription opioids in a county, the prevalence of OUD among older adults may increase (Butler et al., 2016; Hoffman et al., 2019). It should be noted that the average number of physical conditions is negatively associated with the OUD incidence rates in this study. A plausible explanation for this unexpected relationship is that health care providers in counties with high numbers of physical conditions may be more cautious about pain treatment and management than those in counties with low numbers of physical conditions. As such, the OUD incidence rates may be lowered.

Second, our results indicate that high levels of social vulnerability are related to high OUD incidence rates. This association can be partially explained by the differences in social conditions and the characteristics of beneficiaries across counties. Even after taking all covariates, especially social isolation index, age segregation, residential stability, and social capital into account, we still observe the potential linear relationships between SVI quartiles and OUD incidence rates, suggesting that SVI is strongly associated with county-level prevalence of OUD. This finding expands the extant literature on social vulnerability and population health. Specifically, prior research has mainly focused on how social vulnerability is related to physical and mental health outcomes in the general population (Dasgupta et al., 2020; Ganatra et al., 2022) or natural disasters (Flanagan et al., 2011). Few studies have explored substance use outcomes, especially among older adults. This study is among the first to suggest that the county-level OUD incidence rates among older adults are related to SVI.

Third, the correlates of OUD incidence rates vary across the SVI quartiles. Specifically, age segregation is positively associated with the prevalence of OUD only in the third and fourth quartiles, and social capital is only significantly related to the prevalence of OUD in the first and second quartiles. By contrast, the average age of beneficiaries has a consistent and negative association with OUD incidence rates across SVI quartiles. The average HCC score is positively related to the prevalence of OUD, regardless of SVI quartiles. The average number of mental disorders is a significant factor only for the least and the most vulnerable groups. These findings are important as they echo a recent study reporting spatial heterogeneity in the correlates of OUD incidence rates (Yang et al., 2022a). That is, the county-level prevalence of OUD is more sensitive to the changes in certain social conditions or characteristics of beneficiaries in some areas than in others. This study further suggests that heterogeneity exists across the social vulnerability spectrum.

Several sensitivity analyses were conducted to examine the robustness of the findings and conclusions. For example, we duplicated the analyses with 2020 Medicare data and found that our findings were not altered. Moreover, we considered other county-level social conditions, such as rural/urban continuum code (see Author Note 6) and the percentage of the population working in primary industries, but they did not change the findings. We opted not to include them in the analysis for model parsimony. In addition, the multicollinearity test suggested that multicollinearity is not a concern in the analysis. Third, we operationalized the independent variables in different ways (e.g., quartiles or standardization), but our conclusions remained the same. For example, we created the age segregation measure with different age groups (e.g., 75+), and changing the cutoff points does not alter the conclusions (available upon request).

This study is subject to several limitations. First, this is an ecological study; changing the analysis unit (e.g., ZIP codes) may lead to different conclusions (Fotheringham & Wong, 1991; Openshaw, 1984). Although Medicare data can be aggregated into ZIP codes, the social vulnerability index is unavailable at this geography level. Second, the Medicare data do not provide detailed information on beneficiary-level socioeconomic status. As such, we cannot consider variables like average beneficiary income/wealth or percentage of married beneficiaries. Third, it is difficult to compare our findings with those using Medicare data before 2019 because the Substance Use-Disorder Prevention that Promotes Opioid Recovery and Treatment (SUPPORT) for Patients and Communities Act was enacted on January 1, 2020. Under the SUPPORT Act, CMS is allowed to pay for medication for OUD treatment and related services (e.g., counseling), which should increase the number of beneficiaries with OUD and make our dependent variable noncomparable with those collected before 2020. Fourth, the cross-sectional research design does not allow us to make any causal inferences, and the findings cannot be generalized to other age populations. Also, high prevalence of OUD among older adults may increase social vulnerability as the potential tangible and intangible cost to address this issue may increase, a possible reverse causation. Finally, due to data limitations, this study is unable to create SVI for older adults. Developing an age-specific (i.e., older adult) social vulnerability index may allow researchers to better understand the driving force in county-level OUD prevalence.

Some implications can be drawn from this study. First, as social vulnerability is strongly related to OUD incidence rates among older adults, potential interventions that aim to reduce OUD among Medicare beneficiaries can target counties with high levels of social vulnerability. More specifically, local stakeholders need to tailor policies to target different themes of social vulnerability given the variability in the correlates of OUD among older adults. Doing so directly addresses the potential multiscaled and multidimensional processes underlying the county-level OUD spatial patterns (Brazil, 2022; Yang et al., 2022a). Second, in light of the importance of age segregation in highly vulnerable counties, it is important to create opportunities for older adults to interact with younger populations or develop programs like Home Sharing (New York Foundation for Senior Citizens, 2023) that mix older and younger adults. Doing so reduces age segregation and improves both groups' quality of life (Goss, 2022). Third, social capital is negatively associated with the prevalence of OUD, suggesting the importance of social engagement and participation in community organizations/events. Some possible platforms that enhance in-person interactions include building community gardens and hosting neighborhood concerts (Alaimo et al., 2010). For example, engaging in activities related to community gardens has been reported to increase social connections and strengthen social support (Kingsley & Townsend, 2006).

In sum, using the latest Medicare data and social vulnerability index, this study found that social vulnerability is positively associated with the prevalence of OUD in U.S. counties, net of other covariates such as the composition of older Medicare beneficiaries and other social conditions in a county. Furthermore, the correlates of OUD incidence rates vary across SVI quartiles, which suggests that a localized perspective along the social vulnerability spectrum may help reduce OUD among older adults in U.S. counties.

Author Notes

1. Several European countries also experienced declining life expectancy at birth, and scholars have suggested that this phenomenon may be a long-term consequence of the Great Recession around 2008 (Salinari & Benassi, 2022; Salinari et al. 2023). Although little evidence exists in the literature to suggest that the Great Recession directly contributes to the shortened life expectancy in the United States, the compromised local opportunity structures and heightened social/economic inequality associated with the Great Recession may increase social vulnerability and subsequently affect population health.

2. The Federal Information Processing Standard codes for the five counties are 25007, 25019, 36085, 51580, and 53055.

3. The SVI developed by CDC is not specific for older adults. As many indicators in the SVI themes cannot be categorized by age groups, this is a common limitation.

4. We examined the correlations between age segregation and the Household Composition and Disability theme of the SVI and found that their association is weak (Pearson correlation ≈ 0.15).

5. Carpiano (2006) proposed a conceptual framework using Bourdieu's social capital theory to explain the relationship between neighborhood-level social capital and individual-level health outcomes. Although this framework is useful, this study is unable to create a county-level index that fully reflects Carpiano's framework due to data limitations. Similarly, Nicholson and colleagues (2019) used individual-level data to create an older adult social isolation scale, but their scale cannot be duplicated at the county level. The social capital and social isolation indices have been used previously. Future studies should develop other measures for these constructs.

6. The strength of the correlation between metro/nonmetro code and SVI is weak (Pearson correlation ≈ 0.05).

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Conflict of Interest

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Author Contributions

T.- C. Yang developed the research design, supervised the data analysis, and drafted the manuscript. S. Kim conducted all statistical analyses and contributed to revising the manuscript. S. A. Matthews contributed to the development of theoretical arguments, results interpretations, and contributed to revising the manuscript. C. Shoff managed the original data, contributed to drafting the manuscript, and helped interpret findings.

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