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County Social Isolation and Opioid Use Disorder among Older Adults: A Longitudinal Analysis of Medicare Data, 2013–2018

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Abstract

This study aims to fill three knowledge gaps: (1) unclear role of ecological factors in shaping older adults' risk of opioid use disorder (OUD), (2) a lack of longitudinal perspective in OUD research among older adults, and (3) underexplored racial/ethnic differences in the determinants of OUD in older populations. This study estimates the effects of county-level social isolation, concentrated disadvantage, and income inequality on older adults' risk of OUD using longitudinal data analysis. We merged the 2013–2018 Medicare population (aged 65+) data to the American Community Survey 5-year county-level estimates to create a person-year dataset (N = 47,291,217 person-years) and used conditional logit fixed-effects modeling to test whether changes in individual- and county-level covariates alter older adults' risk of OUD. Moreover, we conducted race/ethnicity-specific models to compare how these associations vary across racial/ethnic groups. At the county level, a one-unit increase in social isolation (mean = –0.197, SD = 0.511) increased the risk of OUD by 5.5 percent (OR = 1.055; 95% CI = [1.018, 1.094]) and a one-percentage-point increase in the working population employed in primary industry decreases the risk of OUD by 1 percent (OR = 0.990; 95% CI = [0.985, 0.996]). At the individual-level, increases in the Medicare Hierarchical Condition Categories risk score, physical comorbidity, and mental comorbidity all elevate the risk of OUD. The relationship between county-level social isolation and OUD is driven by non-Hispanic whites, while Hispanic beneficiaries are less sensitive to the changes in county-level factors than any other racial ethnic groups. Between 2013 and 2018, US older adults' risk of OUD was associated with both ecological and individual factors, which carries implications for intervention. Further research is needed to understand why associations of individual factors with OUD are comparable across racial/ethnic groups, but county-level social isolation is associated only with OUD among non-Hispanic white beneficiaries.

Keywords: opioid use disorder, older adults, social isolation, Medicare, Medicaid, fixed-effects modeling, racial/ethnic disparities

1. Introduction

Opioid use disorder (OUD) is a strong predictor of various adverse health outcomes (Blanco and Volkow, 2019), and among older adults having OUD is associated with a higher mortality risk (Larney et al., 2015), more frequent visits to the emergency department (Carter et al., 2019), and higher prevalence of chronic diseases (Torres et al., 2011). Compared with younger or middle-aged populations, older adults are uniquely vulnerable to OUD for several reasons. First, age-related physical changes, such as loss of bone marrow and muscle tissue, make older adults more likely to suffer from physical pain and attend pain clinics (Le Roux et al., 2016; Maree et al., 2016), increasing their chances of being prescribed opioids, a common precursor to the development of OUD (Butler et al., 2016). Second, several life events associated with aging may trigger anxiety and depression (Cacioppo et al., 2006; Cornwell and Waite, 2009) and therefore, older adults may have a strong demand for opioids and a high risk of OUD. For example, retirement and bereavement are associated with the loss of important social roles and increase the feelings of social exclusion and helplessness. These negative emotional reactions have been found to provoke the use of prescription opioids and elevate the risk of opioid abuse (Sullivan et al., 2006). Third, baby-boomers (born between 1946 and 1964) have now entered later life. These individuals lived through an era when alcohol and drugs were more accepted (Le Roux et al., 2016) and they may have more liberal attitudes toward opioid use than previous generations. Furthermore, this cohort has historically tended to overlook the negative consequences of opioid use (Wang and Andrade, 2013) and the signs of OUD (Le Roux et al., 2016). As such, the aging baby-boomers are likely to be at increased risk of OUD. Despite these reasons, OUD among older adults have not drawn much attention until recently (Shoff et al., 2021).

Our understanding of OUD among older adults is limited in at least three ways: underexplored impacts of ecological factors, lack of a longitudinal perspective, and unclear racial/ethnic differences in the determinants of OUD. We explain these gaps as follows. First, while it has been suggested that individual characteristics, such as socioeconomic and employment status, shape the risk of OUD (Sulley and Ndanga, 2020), little research has investigated the potential influence of ecological factors on individual OUD status in older populations. Many scholars have reported that residential environment factors are associated with older adults' physical and mental health outcomes (Arcaya et al., 2016; Barnett et al., 2018; Yen et al., 2009). For example, several studies suggest that low levels of socioeconomic disadvantage in a neighborhood are positively associated with Hispanic older adults' cognitive function and negatively related to mortality and morbidity (Eschbach et al., 2004; Sheffield and Peek, 2009). Similar findings are reported with analyses using data from the general population of older adults (Beard et al., 2009; Michael et al., 2006). Nonetheless, this knowledge stream has mainly focused on cognitive function and mental health (Barnett et al., 2017; Besser et al., 2017; Won et al., 2016), without sufficient attention to older adults' OUD status. Recently, several ecological studies have demonstrated that ecological factors, such as concentrated disadvantage and social isolation, are positively associated with various opioid-related outcomes, such as opioid prescribing to Medicare beneficiaries (Yang et al., 2022), opioid overdose events (Li et al., 2020), and opioid-related overdose deaths (Rushovich et al., 2020). Despite these efforts, little research has investigated how ecological factors affect older adults' risk of OUD.

Among these ecological factors, this study is particularly focused on the role of county-level social isolation in shaping the risk of OUD among older adults for several theoretical reasons. For one, older adults living in areas featured with high levels of social isolation tend to have fewer occasions, opportunities, or organizations that allow them to interact with one another. Older adults' social interactions or relationships may hence be limited and weakened, which is known as the contagion process (Case and Katz, 1991). Consequently, the compromised social relationships and interactions may elevate the risk of OUD among older adults. Moreover, prior research suggests that residential attainment can be regarded as a sorting process based on one's characteristics and preferences (Huang et al., 2017; Wilson, 1987). Therefore, areas with high levels of social isolation may be the result of sorting socially isolated individuals to live in the same areas. This commonality among neighborhood residents may impose a reinforced effect on the risk of OUD. Finally, for older adults who actively participate in social activities or engage in developing social relationships with others, living in areas with high levels of social isolation may reduce the chances of maintaining an active social life. This may eventually erode an individual's social engagement, and increase their risk of OUD. This is comparable to the collective socialization process in which the lack of positive responses may lead to negative outcomes at the individual level (Dietz, 2002).

Beyond the importance of ecological social isolation, the extant literature lacks a longitudinal perspective and has mainly provided short snapshots of OUD and its risk factors. As pointed out in a review article (Maree et al., 2016), most previous research uses cross-sectional data to estimate the prevalence of OUD among older adults or to identify potential risk factors for OUD. These research designs do not allow researchers to evaluate the impacts of risk factors for OUD over time. While some scholars use longitudinal data (Carrière et al., 2015; Larochelle et al., 2018), the time spans tend to be relatively short (e.g., 2 years). Thus, the existing findings provide only a snapshot of concurrent associations of OUD with other factors (Blazer and Wu, 2009; Landreat et al., 2010), and the potential dynamics from a longitudinal perspective remain underexplored.

Lastly, a recent study (Shoff et al., 2021) has documented the racial/ethnic differences in the prevalence of OUD among older adults using the Medicare Beneficiary Summary Files (MBSF) maintained by the Centers for Medicare & Medicaid Services (CMS). Between

2013 and 2018, the overall prevalence of OUD has tripled and the racial/ethnic disparities in the prevalence have widened. For example, in 2013, the prevalence of OUD was 4.6 (per 1,000 beneficiaries) among non-Hispanic whites and 6.3 among non-Hispanic blacks, a gap of 1.7 OUD cases. However, the gap increased to 5 OUD cases (per 1,000 beneficiaries) in 2018 as the prevalence was 15.9 among non-Hispanic whites and 20.9 among non-Hispanic blacks (Shoff et al., 2021). Despite the increasing racial/ethnic disparities in OUD, little research has investigated whether the determinants of OUD vary by race/ethnicity. This question is particularly important because the long-lasting racial/ethnic differences in socioeconomic status (Massey and Eggers, 1990), residential attainment (South et al., 2008), and access to health care (Richardson and Norris, 2010) may shape the risk of OUD differently by race/ethnicity.

The goal of this study is to fill these gaps by answering the following questions: (a) Among older adults, is individual risk of OUD shaped by ecological (i.e., county-level) factors? (b) Among older adults, does the risk of OUD vary in response to the change in both individual factors over time, net of ecological characteristics? and (c) Among older adults, are there any racial/ethnic differences in risk factors for OUD? To achieve the goal, we first assembled a person-year dataset by linking 2013–2018 longitudinal Medicare data to the covariates of residential county and then used conditional logit fixed-effects models to estimate the associations between the risk of OUD and individual- and county-level factors.

2. Data and methods

2.1. Data sources

The individual-level (i.e., beneficiary) variables are drawn from four 2013–2018 CMS MBSF segments: (1) Base, (2) Chronic Conditions, (3) Other Chronic or Potentially Disabling Conditions, and (4) Cost and Utilization. To be included in this analysis, Medicare beneficiaries had to be 65 years of age or older and continuously enrolled in Fee-for-Service Parts A, B, and D for all 12 months of the current year and the previous year. Previous year enrollment was required because of the 2-year reference period used in the OUD measure (see below). Beneficiaries with cancer or in hospice care were excluded from the analysis due to their high use of opioids. There are overall 9,249,288 older beneficiaries in the final analysis. We summarize the selection process and criteria in Figure 1 and note that each beneficiary contributes to at least two observed data points in the analysis. Missing values are rare in the data, so we exclude them from the analysis.

The county-level variables are based on the American Community Survey (ACS) 5-year estimates from 2013 to 2018 and linked to the CMS data by year.[1] For example, the 2009–2013 ACS 5-year data are merged to the 2013 beneficiary data and the 2010–2014 ACS 5-year variables are joined with the 2014 beneficiary data. Doing so allows us to fully exploit the cumulative samples over the 5-year interval collected by the ACS (National Research Council, 2007) and document the annual changes within an individual's county of residence.

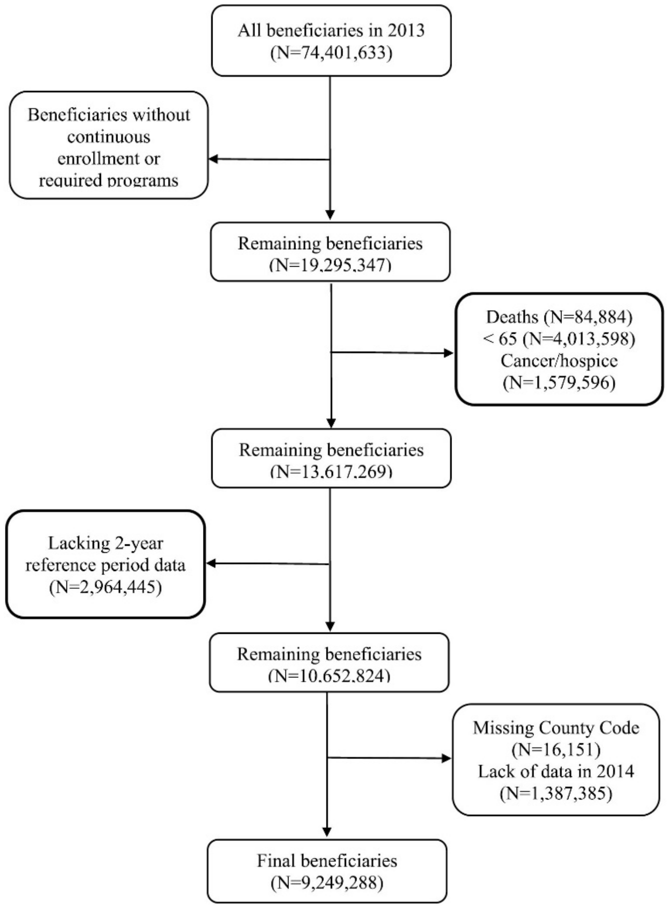

Figure 1. Process and criteria of selecting Medicare older beneficiaries into the final analytic dataset.

2.2. Individual-level variables

The dependent variable is "OUD status," a dummy variable indicating whether a beneficiary has OUD. The OUD status is defined using the MBSF overarching OUD flag,[2] which is included in the Other Chronic or Potentially Disabling Conditions segment. The OUD flag is composed of 3 subindicators: (1) *Diagnosis and procedure basis for OUD*: beneficiaries must have at least one Medicare inpatient claim or two other nondrug claims of any service type with a related code (e.g., counseling) in any position during the 2-year reference period. When 2 claims are required, they must occur at least one day apart. (2) *Opioid-related hospitalization or emergency department (ED) visits*: beneficiaries must have at least one Medicare inpatient claim or one emergency department claim with a related code in any position during the 2-year reference period. (3) *Use of medications for opioid use disorder (MOUD)*: beneficiaries must have one or more drug claim (Medicare Part B, Medicare Part D, and/or Medicaid) with a national drug code (NDC) for MOUD or one or more nondrug claim (Medicare Part B or Medicaid nondrug claim) with a Healthcare Common Procedure Coding

System (HCPCS) code during the 2-year period. When any of the three criteria were met, the beneficiary was defined as having OUD. This definition has been recently used in the literature (Shoff et al., 2021) and a CMS report of OUD (Niles et al., 2020).

We consider four time-varying independent variables in the analysis. First, “dual-eligibility status” is used to determine whether a Medicare beneficiary is also eligible for Medicaid coverage. If s/he is eligible, the dual-eligibility status is coded 1 (dually eligible), otherwise 0 (Medicare only coverage). The MBSF Base segment was used to determine the beneficiary’s dual status every year. Second, the Medicare Hierarchical Condition Categories (“HCC”) risk score is included in the analysis. The HCC scores were developed to understand whether certain beneficiaries are less or more costly to treat than the average population. The CMS has developed an algorithm to gauge beneficiaries’ health risk with multiple factors with an emphasis on 26 distinct disease categories (e.g., infection and liver). Within each category, there are multiple hierarchical health conditions (ranked by severity) and only the most severe condition in each category is used to calculate the HCC score. The HCC scores are normalized to 1.0. Beneficiaries with a score lower than 1 are relatively less costly in the payment system. The HCC score is calculated every year during the study period. Finally, using the MBSF Other Chronic or Potentially Disabling Conditions segment, we create two comorbidity variables, namely “physical comorbidity” and “mental comorbidity.” The former is the sum of four physical conditions: diabetes, hypertension, kidney-related diseases, and chronic obstructive pulmonary disease. The latter is the sum of four mental illnesses: anxiety, depression, bipolar disorder, and schizophrenia/other psychotic disorders. Both variables range from 0 (without any of the conditions) to 4 (having all conditions).

2.3. County-level variables

The beneficiary’s county of residence is identified using the county code variable in the MBSF Base segment. As beneficiaries are likely to move across county boundaries, the county code is updated annually. Even if beneficiaries stay in the same county, there may be changes within the county and the ACS 5-year estimates allow us to measure the within-county changes. At the county level, we created the following variables. Based on a recent report (United Health Foundation, 2018), the social isolation index was generated by averaging the following standardized variables: percent of older householders (ages 65+) who live alone, percent of older adults living in poverty, and percent of older adults with a disability. Higher values indicate higher levels of social isolation. As discussed in the previous section, this social isolation index aims to assess exposures to marginalized populations, under the premise that exposure to such populations places one at risk for social isolation (Gallie et al., 2003). Second, we assessed the socioeconomic conditions of a county with a “concentrated disadvantage” index. This index was constructed by applying the principal component analysis (PCA) technique to the following variables: percent of adults with no high school diploma, percent of female-headed households, child poverty rate, and median household income. The PCA results (see the supplemental file for detailed results) suggest that one factor explains almost 70% of the total variation among these variables and the factor scores based on the PCA analysis represent the levels of concentrated disadvantage, with higher values indicating more disadvantages. We emphasize that the concentrated disadvantage index aims to capture the concentration of disadvantaged general populations and the overall socioeconomic conditions of an area. Furthermore, we consider "income inequality" and "industry component." The former is gauged with the Gini coefficient, which is a common measure of income distribution and ranges between 0 (completely equal) and 1 (completely unequal). The latter is assessed with the percentage of working population employed in primary industry (natural resources, construction, and maintenance).

2.4. Analytic approach and strategy

To take advantage of the longitudinal data, a conditional fixed-effects logistic regression model is used (Allison, 2005). Fixed-effects models allow us to control for all unobserved time-invariant characteristics that might confound the association between the county-level covariates and individual OUD status. By following each respondent over time and capturing changes in variables of interest, each respondent serves as his/her own control and the within-person changes become the focus of the fixed-effects modeling (Allison, 2009). Thus, time-invariant characteristics, such as gender, race/ethnicity, prior educational attainment, and parental background, are omitted from these fixed-effect models. The fixed-effect modeling approach has been the "gold standard" in panel data analysis (Bell and Jones, 2015), given its focus on how the changes in the time-variant independent variables are associated with the changes in the repeatedly observed dependent variables. As such, respondents whose OUD status do not change over time are excluded from the analysis (approximately 10 million beneficiaries do not have any OUD over the study period).[3] To control for temporal trends in both OUD status and the covariates and potential year-specific effects, all models include a set of year dummies with the year of 2018 as the reference year.

A general fixed-effects model can be expressed as follows (Allison, 2005):

$$y_{it} = \mu_t + \beta x_{it} + \alpha_i + \varepsilon_{it},$$

where y_{it} is the dependent variable, OUD status, for individual i at time t; μ_t is an intercept that varies over time; x_{it} is a vector of time-varying independent variables; β is a vector of coefficients for time-varying covariates (e.g., county-level social isolation); α_i is a person-specific error term and can be understood as the systematic influence of all time-invariant factors (including the unobserved covariates) on the dependent variable. One advantage of a fixed-effects model is that it allows us to control for all time-invariant variables, measured or unmeasured, by relying on only within-person differences. Because our dependent variable is binary (e.g., whether a respondent has OUD), the conditional maximum likelihood will be used to estimate the parameters of the conditional logit fixed-effect models and the estimated coefficients can be translated into odds ratios for interpretation (Allison, 2009).

The analytic strategy is divided into three phases. We first conduct a descriptive analysis to compare the data among different racial/ethnic groups. In the second stage, we implement a series of conditional fixed-effects logistic models to understand the associations between OUD status and its covariates for all observations. The first model examines the effects of county-level social isolation on the odds of developing OUD, controlling for the effects of years only. This model serves the baseline model examining if social isolation is associated with OUD. In the second model, other county-level covariates are added to the model, which helps us to understand if other county-level covariates confound with the relationship between social isolation and OUD. The third model further takes dual-eligibility, a proxy for individual socioeconomic status, into account and the HCC score, physical, and mental comorbidity are included in the final model. In the final phase, we create four racial/ethnic groups, namely non-Hispanic whites, non-Hispanic blacks, Hispanics, and non-Hispanic others (including Asians, American Indians/Alaska Natives, and others) and then conduct subgroup analyses by these groups to examine whether and how the results differ by race/ethnicity. All analyses are performed using SAS, and the results are reported in odds ratios (OR) with 95% confidence intervals (95% CIs).

3. Results

Table 1 presents the descriptive statistics for the variables used in this study for all beneficiaries and by the four racial/ethnic groups. We summarize several key findings as follows. First, the one-way ANOVA results suggest that the mean values of all independent variables are significantly different across all racial/ethnic groups (detailed results available upon request). Second, for every 1000 person-years observed, there are 9 OUD records throughout the study period. The prevalence of OUD is the highest among non-Hispanic black beneficiaries (approximately 10 OUD records per 1000 person-years observed). Hispanic (7 per 1000 person-years) and non-Hispanic other (5 per 1000 person-years) beneficiaries report lower prevalence than their non-Hispanic white counterparts. Third, as for county-level covariates, non-Hispanic white and non-Hispanic other beneficiaries tend to live in counties with low levels of social isolation, concentrated disadvantage, and income inequality. By contrast, non-Hispanic black and Hispanic beneficiaries reside in counties featuring undesirable characteristics, such as high isolation and unequal income distribution. Fourth, with respect to beneficiary characteristics, there are stark differences across the groups. For example, 15 percent of all the person-years reported by non-Hispanic whites are dually eligible, but the figure elevates to 53.7 percent for non-Hispanic blacks, 63.4 percent for Hispanics, and 57.9 percent for non-Hispanic others. Similarly, the average HCC score is 1.079 for non-Hispanic white beneficiaries, which is lower than that for non-Hispanic blacks (1.513), Hispanics (1.344), and non-Hispanic others (1.162). Regarding physical comorbidity, racial/ethnic minorities have higher prevalence than non-Hispanic whites. For example, non-Hispanic blacks have, on average, 1.748 physical comorbidities, which is higher than that reported by non-Hispanic whites (1.288). However, mental comorbidity is higher among non-Hispanic whites and Hispanics than other groups.

Table 1. Descriptive statistics of all variables for Medicare older adults in this study, 2013–2018.[a]

	All Beneficiaries		NH Whites		NH Blacks		Hispanics		NH Others	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Dependent Variable										
Opioid Use Disorder	0.009	0.093	0.009	0.094	0.010	0.102	0.007	0.084	0.005	0.069
County-level Socioeconomic Status										
Social Isolation	–0.197	0.511	–0.228	0.489	0.079	0.570	–0.007	0.594	–0.251	0.538
Disadvantage Index	–0.229	0.879	–0.288	0.834	0.303	0.960	0.205	1.010	–0.448	0.967
Income Inequality	0.456	0.035	0.453	0.034	0.474	0.037	0.475	0.037	0.467	0.036
Percent of Population in Primary Industry	9.689	3.440	9.776	3.367	8.915	3.328	10.360	4.342	8.307	3.153
Beneficiary Characteristics										
Dual Medicare and Medicaid	0.225	0.417	0.154	0.361	0.537	0.499	0.634	0.482	0.579	0.494
HCC Score	1.125	1.094	1.079	0.988	1.513	1.708	1.344	1.441	1.162	1.196
Physical Comorbidity	1.341	1.055	1.288	1.040	1.748	1.069	1.572	1.115	1.459	1.066
Mental Comorbidity	0.345	0.680	0.354	0.687	0.309	0.666	0.357	0.692	0.201	0.526
Number of Person-Years	47,291,217		39,510,030		3,043,833		2,659,833		2,077,521	

S.D.: standard deviation

[a]A series of ANOVA and pair-wise group comparison tests suggest that there are significant group differences for all variables across racial/ethnic groups at the 0.001 level. Detailed results are available upon request.

Table 2 presents the results of the nested fixed-effects models for all samples. We first discuss the findings related to social isolation. In Model 1, where we consider social isolation and year dummies only, social isolation is not associated with the odds of having OUD. However, when other county-level characteristics are included in the analysis (Model 2), a positive association between social isolation and OUD status is observed. Specifically, a one-unit increase in the social isolation index is associated with a 3.8% increase in the odds of having OUD (OR = 1.038; 95% CI = [1.002, 1.075]). The positive association remains significant even after controlling for HCC score, physical, and mental comorbidity. In fact, the magnitude of the association between county-level social isolation and the odds of OUD is enhanced after the beneficiary characteristics are included in the final model (OR = 1.055; 95% CI = [1.018, 1.094]), indicating that beneficiaries' characteristics may suppress the relationship between the odds of having OUD and social isolation.

Table 2. Nested fixed-effect regression results with all Medicare older adults in this study, 2013–2018

	Model 1	Model 2	Model 3	Model 4
	Odds ratio (95% CI)	Odds ratio (95% CI)	Odds ratio (95% CI)	Odds ratio (95% CI)
County-Level Socioeconomic Status				
Social Isolation	1.018	1.038*	1.038*	1.055**
	(0.987, 1.049)	(1.002, 1.075)	(1.002, 1.075)	(1.018, 1.094)
Disadvantage Index		0.983	0.983	0.990
		(0.954, 1.012)	(0.954, 1.013)	(0.960, 1.021)
Income Inequality		0.711	0.713	0.595
		(0.417, 1.213)	(0.418, 1.216)	(0.343, 1.035)
Percent of Population in Primary Industry		0.988***	0.988***	0.990***
		(0.983, 0.994)	(0.983, 0.994)	(0.985, 0.996)
Beneficiary Characteristics				
Dual Medicare and Medicaid			1.264***	0.964
			(1.218, 1.311)	(0.928, 1.001)
HCC Score				1.386***
				(1.378, 1.394)
Physical Comorbidity				1.492***
				(1.479, 1.505)
Mental Comorbidity				1.686***
				(1.671, 1.702)
Year (Ref: 2018)				
2013	0.086***	0.086***	0.087***	0.140***
	(0.084, 0.087)	(0.084, 0.087)	(0.085, 0.088)	(0.137, 0.142)
2014	0.120***	0.120***	0.121***	0.183***
	(0.118, 0.122)	(0.118, 0.122)	(0.119, 0.123)	(0.180, 0.186)
2015	0.212***	0.212***	0.213***	0.283***
	(0.209, 0.215)	(0.209, 0.215)	(0.210, 0.216)	(0.279, 0.288)
2016	0.501***	0.502***	0.504***	0.612***
	(0.494, 0.508)	(0.495, 0.509)	(0.497, 0.511)	(0.603, 0.621)
2017	0.836***	0.836***	0.838***	0.918***
	(0.824, 0.848)	(0.825, 0.848)	(0.826, 0.850)	(0.905, 0.931)
AIC	671776.86	671758.18	671600.96	626841.93

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

Regarding other county-level variables, we do not obtain evidence to support that concentrated disadvantage and income inequality are associated with the odds of having OUD over the study period, as the estimated coefficients are not statistically significant from Models 2 to 4. However, the percent of working population employed in primary industry consistently demonstrates a negative association with the odds of having OUD. Specifically, one additional percentage point of working population employed in primary industry reduces the odds of having OUD by 1% in Model 4 (OR = 0.990; 95% CI = [0.985, 0.996]) and this relationship is stable across models.

Furthermore, beneficiary characteristics play an important role in determining the OUD status. As shown in Model 4, the impacts of HCC score, physical, and mental comorbidity are profound. A one-unit increase in a beneficiary's HCC score is associated with a 39-percent increase in the odds of developing OUD (OR = 1.386; 95% CI = [1.378, 1.394]). When a beneficiary reports one additional physical comorbidity, the odds of developing OUD increases by 49% (OR = 1.492; 95% CI = [1.479, 1.505]). The same change in mental comorbidity is associated with a 69 percent increase in the risk of OUD (OR = 1.686; 95% CI = [1.671, 1.702]). Importantly, these health measures seem to account for the detrimental association between dual-eligibility status and the risk of OUD because including these measures in Model 4 renders the estimate of dual-eligibility status nonsignificant.

The estimates of the year dummies demonstrate an increasing pattern of OUD from 2013 to 2017. For example, in Model 4, in contrast to 2018, the odds of developing OUD were 86 percent lower (OR = 0.140; 95% CI = [0.137, 0.142]) in 2013, but this gap has continuously narrowed to approximately 8 percent lower (OR = 0.918; 95% CI = [0.905, 0.931]) in 2017.

To further understand whether the findings above differ by race/ ethnic group, we implement Model 4 by racial/ethnic groups and present the results in Table 3. To avoid redundancy, we summarize the main findings below. First, county-level social isolation is only significant in the non-Hispanic white model, suggesting that our findings in Table 2 are largely driven by non-Hispanic white beneficiaries. The relationship between social isolation and the odds of OUD is stronger in the non-Hispanic white model (OR = 1.069; 95% CI = [1.029, 1.112]) than in Model 4 of Table 2. That is, a one-unit increase in county-level social isolation is related to a 6.9 percent increase in the odds of having OUD among non-Hispanic whites. Second, living in counties with more working population employed in primary industry lowers the odds of having OUD, but this relationship does not hold for Hispanics. Third, changes in physical and mental comorbidity are risk factors for all racial/ethnic groups and the impact of mental comorbidity is stronger than that of physical comorbidity. For example, among non-Hispanic white older adults, one unit change in physical comorbidity is associated with a 50 percent increase in the odds of reporting OUD (OR = 1.497; 95% CI = [1.483, 1.511]), which is weaker than the association with mental comorbidity (OR = 1.709; 95% CI = [1.692, 1.726]).

Table 3. Fixed-effect regression results by Medicare older adults' race/ethnicity (based on Model 4 in Table 2), 2013–2018

	NH Whites	NH Blacks	Hispanics	NH Others
	Odds ratio (95% CI)	Odds ratio (95% CI)	Odds ratio (95% CI)	Odds ratio (95% CI)
County-Level Socioeconomic Status				
Social Isolation	1.069***	0.883	0.978	1.145
	(1.029, 1.112)	(0.767, 1.016)	(0.806, 1.187)	(0.865, 1.516)
Disadvantage Index	0.977	1.122*	1.000	1.026
	(0.946, 1.01)	(1.002, 1.257)	(0.855, 1.169)	(0.820, 1.282)
Income Inequality	0.639	2.328	0.037*	0.029
	(0.354, 1.151)	(0.276, 19.605)	(0.002, 0.686)	(0.000, 2.297)
Percent of Population in Primary Industry	0.991**	0.966**	1.031*	0.940**
	(0.985, 0.997)	(0.943, 0.990)	(1.002, 1.060)	(0.902, 0.979)
Beneficiary Characteristics				
Dual Medicare and Medicaid	0.938**	1.116	1.135	1.178
	(0.900, 0.978)	(0.978, 1.272)	(0.944, 1.365)	(0.877, 1.584)
HCC Score	1.403***	1.248***	1.381***	1.415***
	(1.394, 1.412)	(1.226, 1.271)	(1.346, 1.416)	(1.364, 1.469)
Physical Comorbidity	1.497***	1.425***	1.445***	1.598***
	(1.483, 1.511)	(1.378, 1.473)	(1.387, 1.505)	(1.509, 1.692)
Mental Comorbidity	1.709***	1.417***	1.586***	1.770***
	(1.692, 1.726)	(1.367, 1.469)	(1.519, 1.657)	(1.660, 1.887)
Year (Ref: 2018)				
2013	0.139***	0.152***	0.155***	0.109***
	(0.136, 0.142)	(0.142, 0.163)	(0.142, 0.170)	(0.096, 0.124)
2014	0.181***	0.211***	0.197***	0.154***
	(0.178, 0.185)	(0.198, 0.226)	(0.181, 0.214)	(0.137, 0.173)
2015	0.281***	0.328***	0.301***	0.248***
	(0.276, 0.286)	(0.309, 0.349)	(0.278, 0.325)	(0.223, 0.275)
2016	0.609***	0.669***	0.670***	0.546***
	(0.599, 0.618)	(0.632, 0.709)	(0.624, 0.719)	(0.497, 0.599)
2017	0.918***	0.940*	0.947	0.868**
	(0.903, 0.932)	(0.887, 0.996)	(0.882, 1.016)	(0.792, 0.952)
AIC	539413.50	44391.305	27719.923	14956.550

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

4. Discussion and conclusions

Using the results, we revisit the research questions of this study. First, we obtained evidence to support that individual risk of OUD is shaped by county-level factors. Nonetheless, not all county-level factors were found to be significantly associated with OUD. Specifically, older adults living in counties with high levels of social isolation were shown to have a higher risk of OUD than those residing in counties with low social isolation. By contrast, the percentage of working population employed in primary industry had a protective effect on the risk of OUD. This latter association seems to echo the finding that urban areas have a higher risk of overdose (Kolak et al., 2020) due to the more developed drug environment in urban areas (e.g., availability of illicit drugs). As some scholars suggest that living in rural areas has a higher risk of overdose (Dunn et al., 2016), more effort is warranted to untangle the relationships between rurality and OUD. Concentrated disadvantage and income inequality were not related to the risk of OUD. This finding is somewhat surprising as these two ecological factors have been recently found to affect opioid prescribing patterns and opioid-related mortality (Monnat, 2018; Yang et al., 2022). A possible explanation is that most older adults have social security and retirement benefits (Center on Budget Policy Priorities, 2016) and income inequality among older adults is lower than it is among younger populations (Kuhn and Ríos-Rull, 2016). Older adults may, hence, be little affected by the income inequality or concentrated disadvantage in a county.

The second question is whether the risk of OUD varies in response to the change in individual-level factors over time, net of ecological characteristics. Our results support that when beneficiaries experienced changes in individual-level factors, their risk of OUD alters accordingly and these associations hold after considering county-level variables. In particular, the changes in HCC score and comorbidities show strong associations with OUD, suggesting that worsening health is a strong predictor of OUD. The year dummy variables also indicate that the risk of OUD among older adults increased from 2013 to 2018. Similar findings have been reported in the literature that focuses on the general adult population (e.g., age >20 years old). For example, a study reports that having any mood disorder is strongly associated with the life-time risk of OUD (Saha et al., 2016). Using longitudinal data, Katz et al. (2013) conclude that the increase in physical conditions, such as hypertension and cardiovascular disease, elevates the risk of opioid misuse, abuse, or dependence. It is worth noting that these studies do not consider residential environment factors so that our findings offer evidence suggesting that the effects of both physical and mental comorbidities are robust when accounting for county-level characteristics.

Our third question focused on whether there were any racial/ethnic differences in the risk factors associated with OUD. The race/ethnicity-specific analyses support that county-level factors are more closely related to OUD among non-Hispanic whites than among beneficiaries from other racial/ethnic groups. Social isolation is an apparent example because this county-level factor was only significantly related to OUD among non-Hispanic whites. Among the four racial/ethnic groups, we found that the risk of OUD is least affected by county-level covariates for Hispanics, suggesting that the risk of OUD among Hispanics is mainly shaped by individual-level characteristics, such as health conditions. The heterogeneity in determinants of OUD has also been reported recently. In Florida, researchers report that the opioid-related ED visit rates are the highest among whites and the associations between community characteristics and opioid-related ED visits varies by patients' race/ethnicity (Chen et al., 2021). The racial/ethnic differences may be related to the lack of culturally competent services, potential stigmatization or criminalization of OUD, and under-funded public infrastructure (Siddiqui and Urman, 2022).

Our findings advance the extant literature in several ways. First, we fully take advantage of the longitudinal nature of the Medicare data between 2013 and 2018 by using the fixed-effects modeling. This approach yields robust estimates regarding how the changes in the independent variables affect the changes in the dependent variable, allowing researchers to investigate the determinants of a dependent variable (Allison, 2005). This study, to our knowledge, is among the first to report that county-level social isolation is related to the risk of OUD among older adults and this relationship is only significant among non-Hispanic whites. Second, the null findings regarding concentrated disadvantage and income inequality suggest that these variables may be more relevant to the general population (Monnat, 2018, 2019), rather than older populations. It remains imperative that we identify the risk factors specific to older adults given their unique vulnerability, and the current study is a step in that direction. Third, OUD among older adults has been identified as a hidden aspect of the ongoing opioid crisis (Huhn et al., 2018), as previous research has focused on middle-aged populations (Case and Deaton, 2020). This study demonstrates that the risk of OUD among older adults increases over time and the changes in individual characteristics, especially health and socioeconomic conditions, are important correlates of OUD.

This study is subject to several limitations. First, due to the data limitations, we are unable to know if a Medicare beneficiary has had OUD before s/he enrolled in Medicare. While the fixed-effect modeling approach treats oneself as his/her own control group, it cannot fully address this issue. Second, despite its popularity in panel data analysis, fixed-effect modeling has some limitations, such as limited external validity, potential reverse causality, and unsuitability for comparison with cross-sectional results (Hill et al., 2020). Thus, our findings may not be generalized to other age groups or even older adults who use different types of healthcare insurance. Our findings should be interpreted with these caveats. Third, this study focuses on county-level covariates and our findings and conclusions may be altered when a different geography level is used, such as ZIP code or census tract. This is known as the modifiable areal unit problem (Fotheringham and Wong, 1991). Fourth, several individual-level time-varying covariates are not collected by the CMS, such as marital status and social relationships with family and friends. Our findings may change, should these covariates be included in the analysis. Finally, there is no consensus on how to measure social isolation at the ecological level. Hudson and Doogan (2019) proposed another social isolation index, but their measure aims to target the general population, rather than older populations. While our measure is specific to older adults, using a different measure may lead to different findings.

The limitations above also offer some future research directions. For example, as the middle-aged populations contribute to the ongoing opioid epidemic most (Guy et al., 2017), it is critical to examine if the impact of ecological social isolation holds for this population. Moreover, the potential mechanisms linking county-level social isolation and the risk of OUD should be carefully examined, in order to identify neighborhood- or individual-level factors that can effectively lower the risk of OUD among older adults.

Our findings carry some important policy implications. First, changes in older adults' health conditions and socioeconomic status should be considered in the screening for OUD and this approach is applicable to all older adults, regardless of racial/ethnic backgrounds. We suggest that CMS include screening for OUD in the Health Risk Assessment that is performed at the Medicare Annual Wellness Visit (a yearly no cost visit for Medicare beneficiaries). In addition, residential environment, broadly construed, should be used to identify older adults who have a higher risk of OUD. This is particularly relevant for interventions to improve the receipt of treatment of OUD. For example, with the new Medicare Part B benefit for OUD treatment services furnished by Opioid Treatment Programs (OTPs)[4] that went into effect on January 1, 2020, CMS and Substance Abuse and Mental Health Services

Administration (SAMHSA) could work together to ensure that OTPs are available in residential environments where older adults are likely to be at higher risk of OUD. Finally, the finding that non-Hispanic whites were affected by county-level social isolation is intriguing. Based on our descriptive statistics, non-Hispanic whites have a low level of social isolation, indicating that it is relatively rare for older white beneficiaries to live in communities that are socially isolated. The significant association between social isolation and OUD among non-Hispanic whites, thus, suggests that OUD among older whites happens primarily in places that are socially isolated, whereas among Hispanics, OUD is more evenly spread across geographic areas. As such, while addressing community-level social isolation may help to prevent OUD among white older adults, other strategies are probably needed to prevent OUD among older adults in other racial/ethnic groups.

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Notes

1. Even though ACS releases 1-year estimates over the study period, the geographical coverage is not more than 60% of all US counties, and the usability of the 1-year estimates has been questioned. As such, we opted to use the 5-year estimates in this study.
2. https://www2.ccwdata.org/documents/10280/19140001/oth-cond-algo-oud.pdf
3. Doing so will not bias the coefficient estimates of parameters.
4. This benefit was the result of Section 2005 of the Substance Use-Disorder Prevention That Promotes Opioid Recovery and Treatment for Patients and Communities (SUPPORT) Act.

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