

Geographic, Temporal, and Sociodemographic Differences in Opioid Poisoning



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Introduction: Not enough is known about the epidemiology of opioid poisoning to tailor interventions to help address the growing opioid crisis in the U.S. The objective of this study is to expand the current understanding of opioid poisoning through the use of data analytics to evaluate geographic, temporal, and sociodemographic differences of opioid poisoning—related hospital visits in a region of New York State with high opioid poisoning rates.

Methods: This retrospective cohort study utilized patient-level New York State all-payer hospital data (2010–2016) combined with Census data to evaluate geographic, patient, and community factors for 9,714 Long Island residents with an opioid poisoning—related inpatient or outpatient hospital facility discharge. Temporal, 7-year opioid poisoning rates and trends were evaluated, and geographic maps were generated. Overall, significance tests and tests for linear trend were based upon logistic regression. Analyses were completed between 2017 and 2018.

Results: Since 2010, Long Island and New York State opioid poisoning hospital visit rates have increased 2.5- to 2.7-fold ($p < 0.001$). Opioid poisoning hospital visit rates decreased for men, white patients, and self-payers ($p < 0.001$) and increased for Medicare payers ($p < 0.001$). Communities with high opioid poisoning rates had lower median home values, higher percentages of high school graduates, were younger, and more often white patients ($p < 0.01$). Maps displayed geographic patterns of communities with high opioid poisoning rates overall and by age group.

Conclusions: Findings highlight the changing demographics of the opioid poisoning epidemic and utility of data analytics tools to identify regions and patient populations to focus interventions. These population identification techniques can be applied in other communities and interventions.

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INTRODUCTION

The U.S. is facing a growing opioid crisis.¹ In 2016, an estimated 1.6 million of adults aged ≥ 26 years (0.8% of the population) were affected by heroin or opioid use in the U.S. Use can lead to significant impairment or distress, recurrent social/interpersonal problems, and the potential for chronic relapsing opioid abuse and early death.^{2–5} Between 2005 and 2014, opioid poisoning (OP)—related hospitalizations and emergency room visits increased 64% and 99%, respectively.⁶ Since 2001, opioid-related deaths increased 345%.⁷ In 2016, a total of 63,632 people died in the U.S. from drug

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overdoses, of which 42,249 were from opioids.^{8,9} These data represent a 21% increase in drug overdoses and a 28% increase in opioid-related deaths since 2015.⁹ Historically, the highest nonfatal OP rates nationally were among adults aged 18–34 years, white males, those with lower income, urban-dwelling individuals, and nonprivate payers.^{10–12} These demographics are expanding to include all ages, more women, those with health insurance, higher-income individuals, and midsized cities, suburbs, and rural locations.^{11,13–18} This epidemic is further compounded by the concomitant increase in the incidence of infectious diseases like HIV and hepatitis, thus creating a double burden on the healthcare system.¹⁹ Spatial–temporal evaluations have produced valuable insights into the changing OP patterns by age, race, SES, and urban/rural location; however, they primarily focused on OP deaths at the state or county level, therefore not affording the needed granularity to guide community-based interventions.^{6,18,20–25} ZIP code–level spatial–temporal analyses have further documented urban/rural shifts in the epidemic.^{26,27}

The increased accessibility, prevalence, and misuse of prescription pain relievers, such as hydrocodone and oxycodone, have contributed to this crisis.^{1,28} Between 21% and 29% of individuals who were prescribed opioids for pain misuse them, and 4%–6% transition to heroin.^{29–31} In 2016, fentanyl products were abused by 226,000 people, accounting for some of the largest overdose increases to date.⁴ Opioid-related healthcare, treatment, and criminal justice costs have skyrocketed from \$55.7 billion in 2007 to nearly half a trillion dollars.³²

To combat the epidemic, the HHS has recommended generating better data and conducting research to understand the crisis.^{19,33} In line with this approach, the purpose of this study is to better understand this crisis by using epidemiologic methods and data analytics tools to evaluate geographic, temporal, and sociodemographic differences of OP-related hospital visits in Long Island (LI), a region of New York State (NYS) identified from prior work to have a high OP spatial cluster.³⁴ NYS is one of five states with the highest drug overdose rates, having increased 32.4% from 2015 to 2016.^{6,35} Suffolk County, one of the two counties that comprise LI, had one of the highest rates of opioid overdoses (excluding heroin) in NYS in 2016 with 365 opioid-related deaths.^{36,37} The methods of this study can be applied to other regional data to help understand and intervene in this crisis. Regionally, the study results will serve as the foundation for the development of future focused and targeted OP interventions with an emphasis on optimizing naloxone distribution, which is an effective OP intervention.³⁸

METHODS

This retrospective cohort study used all payer patient–level data from the NY Statewide Planning and Research Cooperative System (SPARCS 2010–2016) in combination with 2010 Census data and American Community Survey LI 5-digit ZIP code–level data.^{39–41} Patients with an OP discharge diagnosis and a NYS home 5-digit ZIP code were included. LI residence was based upon a home ZIP code matching one of 106 Nassau or 113 Suffolk ZIP codes. The NYS Department of Health and Stony Brook University IRB approvals were obtained before data set acquisition and analysis. As the data were obtained from an administrative database maintained by NYS, no informed consent was needed for study participation. All study analyses were completed between 2017 and 2018.

Study Sample

The data set included patient-level demographics, diagnoses, treatments, services, and charges for all inpatient and outpatient services provided by NYS licensed healthcare facilities. Starting on January 1, 2016, SPARCS began including standalone laboratory and radiologic claims, which resulted in an overall increase in outpatient claims and data volume.⁴²

This study included 3,426,563 patients (Nassau, 1,636,758; Suffolk, 1,789,805) seen at any facility treatment location (i.e., inpatient, outpatient, emergency room, ambulatory surgery). These inclusion criteria expanded upon those used by NYS to reflect all patients presenting with OP.⁴¹ Patient records were selected utilizing ICD-9 (January 1, 2010–September 30, 2015) and ICD-10 (October 1, 2015–December 31, 2016) discharge diagnostic codes (i.e., principal and 24 other diagnostic codes) with SPARCS-defined keywords, such as *opiates*, *opium*, *heroin*, *methadone*, and other related narcotics (Appendix Table 1, available online).^{36,42,43} The cohort was then aggregated by 5-digit ZIP code for all further analyses to ensure de-identification and preserve confidentiality. Patients with a non-NYS home ZIP code were excluded. An initial analysis was completed to reproduce NYS analyses for hospitalization and emergency room OP visits that excluded sequela codes to confirm the accuracy of the data capture methods.^{41,43}

Measures

Patient factors (age, sex, race, ethnicity, method of payment) were obtained directly from SPARCS. Community factors (population density, land area, home values, income, age, sex, race, ethnicity, employment, education) for each 5-digit ZIP code were obtained from the 2010 Census. Population density and land area were used as proxies for urban/rural differences.

East of New York City, LI comprises two independently governed suburban counties: Nassau to the west and Suffolk to the east. The ZIP code–specific demographic data were obtained from American FactFinder (Appendix Table 2, available online).^{39–41} In 2010, a total of 2.82 million people lived on LI with little population change since then.⁴⁰ Although Nassau and Suffolk are approximately equal in population size, the population density per square mile of land area in Nassau is almost three times higher than that in Suffolk. Both counties are similar in age, sex, and Latinx heritage. Nassau is more diverse by race and more educated. Median home values and median household income were higher in Nassau than Suffolk. Since 2010, although regional home values dropped, income rose.

Statistical Analysis

The patient served as the unit of analysis to ensure that patients with multiple visits within 1 year did not over contribute their data to per-year or 7-year summary analyses. Thus, only the first OP-related visit for each patient in each year was included in per-year analyses; only the first OP-related visit independent of year was included in the 7-year summary analysis. Trends for multiple OP visits within any 1 year were analyzed separately.

Overall, crude and age-stratified rates of OP were calculated as the outcome measures calculated per 10,000 population. Crude rates were calculated based upon per-year and 7-year patient-level OP-related healthcare facility visits as the numerator and 2010 Census population figures per ZIP code as the denominator. For inclusion in the geographic maps, ZIP code–level crude rates of 7-year incidence were calculated using the Census data per ZIP code. Age-stratified rates were calculated for age strata (20–39 years, 40–59 years, and ≥ 60 years) using reported patient ages in the numerators and age/ZIP code–specific Census data in the denominators to adjust for ZIP code–level differences by age.⁴⁰ Individuals aged ≥ 105 years were considered age outliers and excluded from age-stratified analyses. The crude and age strata rates calculated per ZIP code were divided into quartiles (Q). For analysis and mapping purposes, the lowest two quartiles were collapsed (Q1/2), as in the preliminary analyses there were no significant differences between Q1 and Q2, and compared with Q3 and Q4 (highest OP rates) separately.

The 5-digit home ZIP codes and addresses of patients were combined with TIGER/LINE geographic data to accurately generate the ZIP code–level geographic maps using the software ArcGIS Desktop, version 10.5.^{34,44} Geographic maps were restricted to individuals aged ≥ 20 years because of the small numbers of younger patients.

Dichotomous outcomes (e.g., percentage male) were fitted as dependent variables in logistic regression models for 7-year and ZIP code quartile differences. The year or ZIP code quartile was included as explanatory variables. ANOVA models were fit for continuous outcomes (e.g., age) with the inclusion of year or quartiles as explanatory variables. Overall significance was determined based on *F*-tests from logistic regression or ANOVA. Linear trends were evaluated using contrast *F*-tests based on logistic regression or ANOVA. Significant results were defined at $p \leq 0.05$. All statistical analyses used SPSS, version 24, or SAS, version 9.3.

RESULTS

The number and rates of OP-related inpatient and outpatient healthcare facility visits significantly increased ($p < 0.001$; linear trend, $p < 0.001$) from 2010 to 2016 for NYS (2.7-fold), Nassau (2.7-fold), and Suffolk (2.5-fold; Table 1). Inclusion of OP as a sequela code resulted in an increase in OP cases per year compared with NYS reports.⁴² OP rates for 2016 increased 111% for Nassau and 54% for Suffolk over those previously reported where OP cases were defined using only the principal and first listed cause.^{41,43} During the 7-year evaluation period, Suffolk rates remained higher, and Nassau rates, lower than NYS. OP rates between 2015 and 2016 almost doubled for each county and for NYS. From 2010 to

2016, the demographics of OP patients by sex and race significantly changed for NYS and each county; significant changing trends by ethnicity were observed for Nassau and NYS. The percentage of patients using self-pay significantly decreased whereas the percentage using Medicare increased across LI and NYS. Use of Medicaid significantly decreased in Nassau and NYS and increased in Suffolk. Significant linear trends between 2010 and 2016 were observed for each county and NYS overall for race and self-pay with linear decreases in the percentage of white patients and self-pay. Linear trends for other factors differed by factor and location.

From 2010 to 2016, a total of 8,615 NYS residents presented multiple times with OP (14.8% of all patients with OP; rate, 4.45/10,000 population). The percentages and rates for Nassau were lower and for Suffolk higher than NYS (Nassau, 12.4% [3.04/10,000 population]; Suffolk, 16.8% [7.23/10,000 population]). No additional results are reported for this subgroup because the number of patients from LI with multiple OP visits in any 1 year was too small for detailed subgroup analysis (range, 5%–10% of all patients; 16–218 people).

Crude OP rates ranged from 0 to 588.24 per 10,000 population. Quartile ranges were higher in Suffolk, but a single Nassau ZIP code had the overall highest crude rate compared with Suffolk (588.24 vs 529.80 per 10,000 population).

The Q4 ZIP codes in both Nassau and Suffolk had communities with the lowest median home value, greatest percentage of residents who completed high school, and lowest percentage of residents who achieved education beyond college. In Nassau, Q4 ZIP codes were significantly associated with communities that had a greater percentage of white residents (Q1/2, 73%; Q3, 76% vs Q4, 89%; $p = 0.008$). In Suffolk only, lower median income was significantly associated with Q4 ZIP codes.

Differences were observed between OP rate quartiles both within and between counties (Table 2). OP patients in each county with a home residence within Q4 were significantly younger and more often identified themselves as white ($p \leq 0.001$). Individuals residing in Nassau Q4 ZIP codes were significantly more frequently male ($p = 0.006$) and more likely to pay with Medicaid ($p < 0.001$). OP patients from Suffolk Q4 ZIP codes were significantly more likely to use self-pay only ($p < 0.001$) and less likely to use Medicare ($p = 0.007$). Each of these factors had a significant linear trend between quartiles.

The OP patients were more concentrated on Nassau's south shore and in Suffolk's western section, where population densities are higher than other regions of each county (Appendix Figure 1, available online). When controlling for population size, the highest crude OP rates in Nassau remained on the south shore (Figure 1A)

Table 1. Patient Rates and Factors of OP-Related Hospital Visits in LI and NYS (2010–2016)

Variable	Individual year ^a							p-value		All years unique patient count ^b
	2010	2011	2012	2013	2014	2015	2016	Overall ^c	Linear trend ^c	
Nassau County										
Unique patient visits, <i>n</i>	379,094	421,612	429,959	430,871	444,769	460,590	517,528	—	—	1,636,758
Opioid poisoning, <i>n</i> (%)	306 (0.08)	331 (0.08)	311 (0.07)	408 (0.09)	516 (0.12)	591 (0.13)	1,147 (0.22)	—	—	3,327 (0.20)
Rate per 10,000 population ^d	2.3	2.4	2.3	3.0	3.8	4.4	8.5	<0.001	<0.001	24.6
Age, years, mean (SD) ^e	41.7 (18.9)	40.9 (18.1)	39.6 (17.3)	38.6 (17.4)	39.0 (18.5)	43.5 (20.1)	50.0 (21.7)	0.93	0.28	44.1 (20.4)
Sex, male, <i>n</i> (%)	183 (59.8)	183 (55.3)	187 (60.1)	254 (62.3)	347 (67.2)	334 (56.5)	603 (52.6)	<0.001	0.62	1,901 (57.1)
Race, white, <i>n</i> (%)	273 (89.2)	296 (89.4)	273 (87.8)	352 (86.3)	443 (85.9)	494 (83.6)	937 (81.7)	0.001	0.003	2,809 (84.4)
Ethnicity, Hispanic, <i>n</i> (%)	43 (14.1)	53 (16.0)	48 (15.4)	39 (9.6)	47 (9.1)	44 (7.4)	118 (10.3)	<0.001	<0.001	371 (11.2)
Self-pay (only), <i>n</i> (%)	40 (13.1)	40 (12.1)	26 (8.4)	45 (11.0)	47 (9.1)	29 (4.9)	48 (4.2)	<0.001	<0.001	253 (7.6)
Medicare (any), <i>n</i> (%)	81 (26.5)	73 (22.1)	68 (21.9)	72 (17.6)	104 (20.2)	157 (26.6)	414 (36.1)	<0.001	0.99	908 (27.3)
Medicaid (any), <i>n</i> (%)	88 (28.8)	117 (35.3)	93 (29.9)	128 (31.4)	157 (30.4)	194 (32.8)	279 (24.3)	<0.001	0.96	943 (28.3)
Suffolk County										
Unique patient visits, <i>n</i>	446,423	492,702	501,252	504,410	522,438	536,608	618,066	—	—	1,789,805
Opioid poisoning, <i>n</i> (%)	625 (0.14)	691 (0.14)	709 (0.14)	835 (0.17)	910 (0.17)	1,301 (0.24)	2,187 (0.35)	—	—	6,387 (0.36)
Rate per 10,000 population ^d	4.2	4.6	4.8	5.6	6.1	8.7	14.7	<0.001	<0.001	43.0
Age, years, mean (SD) ^e	38.0 (17.7)	37.1 (16.0)	36.8 (16.7)	36.4 (16.2)	36.7 (17.1)	39.0 (18.1)	43.6 (20.0)	0.95 ^e	0.32 ^e	39.8 (18.7)
Sex, male, <i>n</i> (%)	371 (59.4)	414 (59.9)	438 (61.8)	520 (62.3)	587 (64.5)	809 (62.2)	1,259 (57.6)	0.008	0.08	3,794 (59.4)
Race, white, <i>n</i> (%)	547 (87.5)	595 (86.1)	613 (86.5)	714 (85.5)	759 (83.4)	1,080 (83.0)	1,796 (82.1)	0.003	0.001	5,324 (83.4)
Ethnicity, Hispanic, <i>n</i> (%)	68 (10.9)	85 (12.3)	75 (10.6)	98 (11.7)	109 (12.0)	118 (9.1)	268 (12.3)	0.12	0.35	736 (11.5)
Self-pay (only), <i>n</i> (%)	159 (25.4)	139 (20.1)	156 (22.0)	160 (19.2)	131 (14.4)	153 (11.8)	221 (10.1)	<0.001	<0.001	1,006 (15.8)
Medicare (any), <i>n</i> (%)	119 (19.0)	131 (19.0)	124 (17.5)	131 (15.7)	163 (17.9)	243 (18.7)	564 (25.8)	<0.001	0.94	1,316 (20.6)
Medicaid (any), <i>n</i> (%)	180 (28.8)	219 (31.7)	191 (26.9)	288 (34.5)	305 (33.5)	449 (34.5)	718 (32.8)	0.005	0.002	1,994 (31.2)
New York State										
Unique patient visits, <i>n</i>	6,237,733	7,627,859	7,612,980	7,652,722	7,738,133	7,939,937	9,237,514	—	—	24,930,165
Opioid poisoning, <i>n</i> (%)	5,438 (0.09)	6,165 (0.08)	6,592 (0.09)	7,286 (0.10)	7,984 (0.10)	11,114 (0.14)	20,147 (0.22)	—	—	58,402 (0.23)
Rate per 10,000 population ^d	2.8	3.2	3.4	3.8	4.1	5.7	10.4	<0.001	<0.001	30.1
Age, years, mean (SD) ^e	41.7 (17.5)	41.2 (17.5)	41.4 (17.5)	40.5 (17.3)	40.3 (17.2)	42.7 (18.8)	47.4 (20.3)	0.95 ^e	0.33 ^e	43.6 (19.2)
Sex, male, <i>n</i> (%)	2,979 (54.8)	3,490 (56.6)	3,745 (56.8)	4,280 (58.7)	4,770 (59.7)	6,435 (57.9)	10,799 (53.6)	<0.001	<0.001	32,446 (55.6)
Race, white, <i>n</i> (%)	3,984 (73.3)	4,492 (72.9)	4,819 (73.1)	5,254 (72.1)	5,853 (73.3)	7,937 (71.4)	13,820 (68.6)	<0.001	0.006	41,335 (70.8)
Ethnicity, Hispanic, <i>n</i> (%)	609 (11.2)	665 (10.8)	778 (11.8)	957 (13.1)	921 (11.5)	994 (8.9)	2,012 (10.0)	<0.001	0.002	6,301 (10.8)
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Table 1. Patient Rates and Factors of OP-Related Hospital Visits in LI and NYS (2010–2016) (continued)

Variable	Individual year ^a							p-value		All years unique patient count ^b
	2010	2011	2012	2013	2014	2015	2016	Overall ^c	Linear trend ^c	
Self-pay (only), n (%)	890 (16.4)	949 (15.4)	1,041 (15.8)	1,050 (14.4)	948 (11.9)	940 (8.5)	1,368 (6.8)	<0.001	<0.001	6,610 (11.3)
Medicare (any), n (%)	1,171 (21.5)	1,289 (20.9)	1,418 (21.5)	1,497 (20.5)	1,617 (20.3)	2,603 (23.4)	6,079 (30.2)	<0.001	0.002	14,345 (24.6)
Medicaid (any), n (%)	2,275 (41.8)	2,554 (41.4)	2,535 (38.5)	2,847 (39.1)	3,369 (42.2)	4,611 (41.5)	7,643 (37.9)	<0.001	0.80	22,640 (38.8)

Note: Boldface indicates statistical significance ($p < 0.05$).

^aNumber and percent of unique patient-level healthcare facility encounters for opioid poisoning; count based upon first opioid-related hospital visit within each year for each county and for NYS overall.

^bNumber and percent of unique patient-level healthcare facility encounters for opioid poisoning; count based upon first opioid-related healthcare facility related visit occurring at any time between 2010 and 2016.

^cp-values are based on logistic regression for n (%) with the exception of age, which is compared using ANOVA.

^dRates are calculated based upon per-year and 7-year patient-level opioid-related healthcare facility visits as the numerator and population figures from the 2010 Census as the denominator per 10,000 population.

^eMean ages are computed across the full age range from newborn to 104 years. Age is compared between years using ANOVA.

LI, Long Island; NYS, New York State; OP, opioid poisoning.

but shifted to a more central area in Suffolk (Figure 2A). The Q4 ZIP code patterns differed by age strata within each county (Appendix Table 3, available online; Nassau, Figure 1B–D; Suffolk, Figure 2B–D). In Nassau, the differences between Q3 and Q4 age strata of 40–59 years and ≥ 60 years were not statistically significant. In Suffolk, Q3 and Q4 were significantly different for all age strata ($p < 0.01$).

DISCUSSION

This study helps address gaps in understanding the opioid crisis by utilizing epidemiologic and data analytics methods to evaluate geographic, temporal, community, and personal demographics of OP patients from LI. The reported temporal OP use trends agree with the Centers for Disease Control and Prevention—reported trends that noted significant increases in overall use and use by female individuals, older adults, and non-Hispanic whites (2003–2014).^{11,13,45} ZIP code—specific housing values and income below the countywide average showed similar distribution patterns with Q4 OP ZIP codes and correspond with national data correlating OP with lower SES (lower home prices, income, and educational attainment).¹³ Even though home values and income were not adjusted for regional cost of living differences, the observed trends are consistent with national statistics of higher opioid use among lower-income households. The current study identifies significant increases in the percentage of women (Δ Nassau, +7.2%; Suffolk, +1.8%; NYS, +1.2%), percentage of minority populations (Δ Nassau, +7.5%; Suffolk, +5.4%; NYS, +4.7%), and decreases in out-of-pocket payment (Δ Nassau, –8.9%; Suffolk, –15.3%; NYS, –9.6%). The aging U.S. population overall and enactment of the 2014 Affordable Care Act may clarify the observed change in payment methods.⁴⁶ Opioid prescribing among Medicare part D recipients has risen 2.84% in NYS, which may explain the association with Medicare.⁴⁷ Age has also been associated with different opioid use patterns.⁴⁸ States with higher median population age consume more opioids per capita, suggesting that older adults consume more opioids.⁴⁹ The different age-specific mapping patterns identified herein may reflect differing community age structures and should guide tailoring interventions to community needs.

Through the successful identification of LI OP patient demographics and communities in greatest need, the findings from this study are now helping regional efforts to plan for and expand capacity to provide focused and targeted OP interventions where they are needed the most. With naloxone (opioid antagonist) demand higher than supply, focusing on naloxone

Table 2. Patient and Community Factors Related to Crude Rate Quartile of OP in LI County (2010–2016)

Variable	Crude rate quartile cut-points of OP				p-value ^a	
	Quartiles 1 and 2	Quartile 3	Quartile 4	Overall	Linear trend	
Nassau County						
Range per quartile per 10,000 population	≤21.33	21.34–30.09	30.10–588.24	—	—	
Community factor (Census data) ZIP codes, <i>n</i>	35	18	17	—	—	
Population density (persons per square mile), mean (SD)	6,249.1 (6,723.3)	5,717.4 (3,260.0)	5,353.0 (2,681.1)	0.83	0.55	
Land area (square miles), mean (SD)	4.1 (3.3)	4.2 (2.5)	3.7 (3.3)	0.89	0.78	
Median home value, US\$, mean (SD)	631,464 (214,388)	515,906 (141,298)	480,381 (111,437)	0.01	0.003	
Median income, US\$, mean (SD)	113,005 (31,721)	98,255 (22,502)	97,019 (9,194)	0.06	0.02	
Median age, years, mean (SD)	41.1 (10.4)	42.2 (3.4)	44.2 (3.9)	0.41	0.21	
Sex, male, mean% (SD)	47.6 (3.7)	48.5 (0.7)	51.3 (12.6)	0.18	0.09	
Race, white, mean% (SD)	73.0 (20.3)	76.0 (19.9)	89.4 (6.0)	0.01	0.008	
Ethnicity, Hispanic, mean% (SD)	11.7 (10.1)	13.6 (12.1)	9.3 (4.7)	0.45	0.70	
Employment status, working full-time, mean% (SD)	38.6 (10.8)	42.1 (3.5)	44.4 (3.6)	0.06	0.02	
Education, <high school, mean% (SD)	8.5 (7.4)	9.9 (8.5)	7.5 (2.9)	0.59	0.88	
Education, high school graduate, mean% (SD)	32.4 (12.5)	38.7 (8.9)	42.7 (9.8)	0.008	0.002	
Education, beyond bachelor's degree, mean% (SD)	25.2 (12.8)	19.1 (8.8)	16.9 (9.1)	0.03	0.008	
Patient factor (SPARCS data) unique patients, <i>n</i>	496	979	1,852	—	—	
Age, years, mean (SD) ^b	44.8 (21.2)	45.4 (20.0)	42.5 (20.0)	0.001	0.02	
Sex, male, <i>n</i> (%)	603 (54.3)	538 (55.9)	760 (60.6)	0.006	0.03	
Race, white, <i>n</i> (%)	874 (78.7)	771 (80.1)	1,164 (92.8)	<0.001	<0.001	
Ethnicity, Hispanic, <i>n</i> (%)	105 (9.5)	111 (11.5)	155 (12.4)	0.08	0.04	
Self-pay (only), <i>n</i> (%) ^c	79 (7.1)	64 (6.6)	110 (8.8)	0.12	0.59	
Medicare (any), <i>n</i> (%) ^c	294 (26.5)	286 (29.7)	328 (26.2)	0.14	0.39	
Medicaid (any), <i>n</i> (%) ^c	263 (23.7)	336 (34.9)	344 (27.4)	<0.001	<0.001	
Suffolk County						
Range per quartile per 10,000 population	≤38.34	38.35–50.64	50.65–529.80	—	—	
Community factor (Census data) ZIP codes, <i>n</i>	54	27	26	—	—	
Population density (persons per square mile), mean (SD)	1,624.3 (1,434.4)	2,193.9 (2,054.0)	2,276.5 (1,556.2)	0.16	0.06	
Land area (square miles), mean (SD)	8.6 (8.0)	8.7 (7.0)	8.1 (10.3)	0.96	0.85	
Median home value, US\$, mean (SD)	560,698 (201,510)	460,492 (180,798)	366,977 (109,147)	<0.001	<0.001	
Median income, US\$, mean (SD)	98,372 (21,971)	88,989 (18,737)	78,136 (17,863)	<0.001	<0.001	
Median age, years, mean (SD)	43.9 (7.0)	42.0 (4.1)	41.4 (5.6)	0.19	0.07	
Sex, male, mean% (SD)	50.1 (7.2)	49.8 (2.0)	49.3 (1.4)	0.84	0.58	
Race, white, mean% (SD)	85.2 (19.6)	85.8 (9.8)	87.4 (8.7)	0.84	0.59	

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Table 2. Patient and Community Factors Related to Crude Rate Quartile of OP in LI County (2010–2016) (continued)

Variable	Crude rate quartile cut-points of OP				p-value ^a	
	Quartiles 1 and 2	Quartile 3	Quartile 4	Overall	Linear trend	
					Overall	Linear trend
Ethnicity, Hispanic, mean% (SD)	10.7 (12.4)	13.0 (9.0)	11.3 (6.0)	0.63		0.57
Employment status, working full-time, mean% (SD)	39.8 (8.7)	40.4 (8.4)	42.5 (9.0)	0.41		0.23
Education, <high school, mean% (SD)	6.9 (6.9)	9.2 (5.9)	8.5 (5.5)	0.24		0.14
Education, high school graduate, mean% (SD)	39.7 (10.2)	47.4 (10.0)	54.6 (12.2)	<0.001		<0.001
Education, beyond bachelor's degree, mean% (SD)	19.8 (9.7)	14.4 (7.1)	10.4 (5.1)	<0.001		<0.001
Patient factor (SPARCS data) unique patients, <i>n</i>	706	1,625	4,056	—		—
Age, years, mean (SD) ^b	41.2 (20.0)	39.6 (18.6)	39.0 (17.7)	<0.001		<0.001
Sex, male, <i>n</i> (%)	1,149 (57.9)	1,053 (59.6)	1,592 (60.4)	0.23		0.12
Race, white, <i>n</i> (%)	1,596 (80.4)	1,490 (84.3)	2,238 (85.0)	<0.001		<0.001
Ethnicity, Hispanic, <i>n</i> (%)	242 (12.2)	204 (11.5)	290 (11.0)	0.45		0.27
Self-pay (only), <i>n</i> (%) ^c	219 (11.0)	266 (15.0)	521 (19.8)	<0.001		<0.001
Medicare (any), <i>n</i> (%) ^c	452 (22.8)	364 (20.6)	500 (19.0)	0.007		0.006
Medicaid (any), <i>n</i> (%) ^c	621 (31.3)	572 (32.4)	801 (30.4)	0.37		0.94

Note: Boldface indicates statistical significance ($p < 0.05$).

^ap-values are based on ANOVA for mean (SD) and logistic regression for *n* (%).

^bMean ages are computed across the full age range from newborn to 104 years.

^cPayer information was not mutually exclusive. Method of payment was defined as “self-pay” only if no other insurance type was listed in SPARCS. Medicare and Medicaid were included if either or both were listed in the database as a method of payment.

LI, Long Island; OP, opioid poisoning; SPARCS, New York Statewide Planning and Research Cooperative System.

distribution to professionals and “likely bystanders” within identified high-rate communities has the potential for the strongest impact on OP outcomes.^{38,50–52}

Existing specialized opioid treatment and evidence-based psychosocial programs such as the Vermont Hub and Spoke, clinic-based medication-assisted therapy, and the Project Extension for Community Healthcare Outcomes (ECHO) virtual clinics have successfully utilized an integrated team approach to support opioid management nationwide. Regional challenges to implementation of such programs include limited trained personnel to deliver such programs and the shortage of trained and waived buprenorphine prescribers.^{26,28,53–58} To help address provider shortage, the Opioid Crisis Response Act of 2018 includes provisions to support provider education and training.⁵⁹ The knowledge gained from the current study of local communities in need provides the first critical step in addressing provider shortages. Local practitioner shortages are starting to be addressed by focusing outreach efforts on integrated workforce training and exploring the use of ECHO telehealth services to reach identified underserved populations in need of treatment programs.

Another way the mapping data can be used is to correlate opioid prescriber patterns with OP rates. The NYS Internet System for Tracking Over-Prescribing (I-STOP) prescription drug monitoring program documented changes in opioid-related outcomes, though individual community-level effect of the program was not explored.⁶⁰ The study team plans to evaluate the inter-relationship between opioid prescribing and LI OP rates to help focus on future regional opioid prescribing continuing education programs.

Methods used to prepare, analyze, and visualize the data show useful techniques to help understand and address the epidemic. SPARCS provided sufficient sample size to conduct evaluations by ZIP code. NYS cautions that findings generated from these data potentially under-report the burden of opioid abuse and dependence in NYS.³⁶ The current study shows a potential source to improve OP reporting by including all listed OP diagnoses in analyses. These findings need to be replicated with similar data sets from other states to fully understand the extent of OP under-reporting. This model of informing and targeting health interventions has the potential to optimize service provisions to address the regional opioid crisis with applicability to other U.S. regions nationwide.

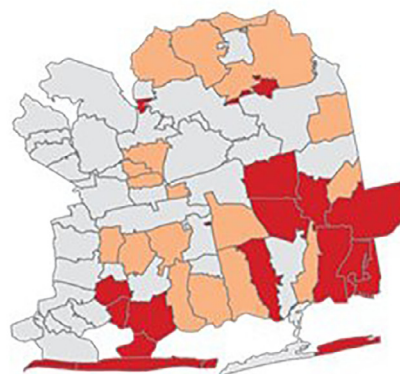
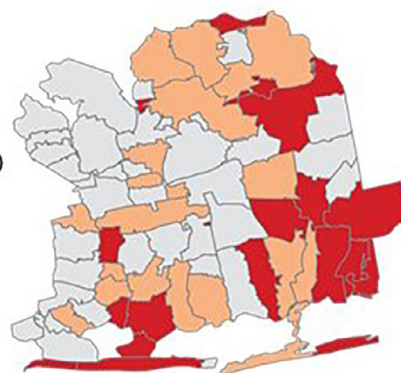
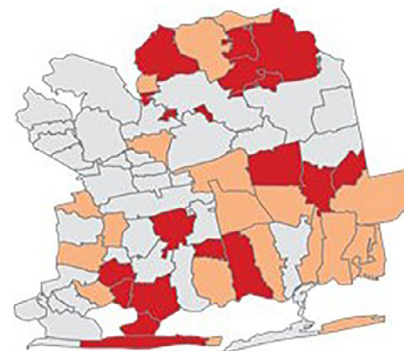
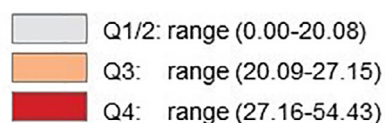
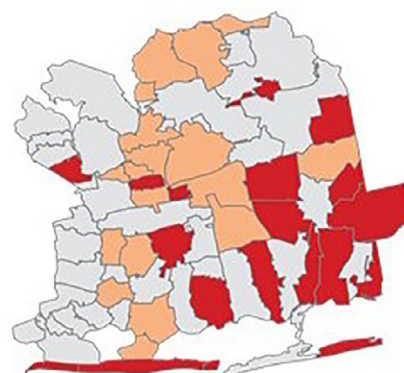
A Crude Rates**B 20-39 year old age group****C 40-59 year old age group****D ≥60 year old age group**

Figure 1. Nassau County Overall and Age-Stratified Rates of Opioid Poisoning by ZIP Code (2010–2016).

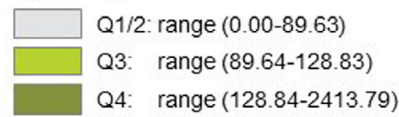
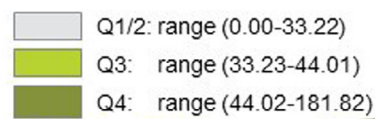
A Crude Rates**B 20–39 year old age group****C 40–49 year old age group****D ≥60 year old age group**

Figure 2. Suffolk County Overall and Age-Stratified Rates of Opioid Poisoning by ZIP Code (2010–2016).

LIMITATIONS

Using all-payer databases has some limitations. OP patients who either are treated or die outside of a health-care facility are excluded, resulting in possible under-reporting of OP. In 2015, LI coroners' data included 12% of deaths attributed to OP ($n=51$) not included in SPARCS.^{36,37} Transition to ICD-10 in the later part of 2015 could account for about 14% of the increased rates observed during the transition, and 3.5% of the increased rates in 2016 owed to these coding changes.⁶¹ Increased OP rates may be attributed to more individuals seeking care at the hospital during this period and may not be reflective of changing general population OP rates. Though rates for ZIP codes with small populations may not be stable with yearly variability, quartile analysis did not change quartiles for these ZIP codes.

Lack of granularity with respect to individuals and the ability to examine interactions with coexisting factors external to the patient is inherent with large single-source data sets. There is no definitive information on opioid source or reason for use. Prospective medical records analysis is required to further understand the relationships among individuals' medical, opioid and social history, treatment, and the underlying reasons for prescription or illicit drug use/abuse.

CONCLUSIONS

Between 2010 and 2016, LI OP rates increased by >250%, documenting the growing regional opioid crisis. The bicounty commonalities and differences in community and personal OP-related factors support the importance of understanding and intervening at the community level, focusing on those at most risk. Maps highlight the geographic distribution of OP rates by ZIP code, facilitating community stakeholder discussions of otherwise complex analyses for developing grassroots community action plans. The strength of multidisciplinary collaborations and the role of data analytics methods provide a collaborative approach to planning and action to address a crisis affecting LI and with applicability to other U.S. communities.

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All authors contributed to the conception, design, and conduct of the study and interpretation of study findings. FW, XC, and YW generated the geographic maps; WH, ERS, and YW performed all data analyses. SR completed quality control analyses to confirm data analytics methods. ERS, GSL, and YW contributed equally

to this manuscript and wrote the initial draft. All authors reviewed, revised, and approved the final manuscript.

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SUPPLEMENTAL MATERIAL

Supplemental materials associated with this article can be found in the online version at <https://doi.org/10.1016/j.amepre.2019.03.020>.

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