6-19-2023

Neighborhood Disadvantage and Pediatric Inpatient Opioid Prescription Patterns

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Recommended Citation

Kranjac, A. W., Kranjac, D., Kain, Z. N., Ehwerhemuepha, L., Donaldson, C., & Jenkins, B. N. (2023). Neighborhood disadvantage and pediatric inpatient opioid prescription patterns. *Journal of Pediatric Nursing, 72*, e145-e151. https://doi.org/10.1016/j.pedn.2023.06.021

Neighborhood disadvantage and pediatric inpatient opioid prescription patterns

Introduction

The frequency of opioid prescribing for acute pain management among children in the United States increased between the mid-1990s and mid-2000s before the rates stabilized from the mid-2000s to mid-2010s (Mazer-Amirshahi et al., 2014). Despite a decrease in opioid prescribing to children after the mid-2010s, the rates continue to be greater than those reported in other developed nations (McCabe et al., 2017). Researchers studying pediatric opioid prescribing patterns frequently focus on individual indicators that associate with the frequency of opioid prescriptions. For example, opioid dispensing rates for children aged 0–17 years vary by patient-level factors such as race/ethnicity, age, admission type (e.g., inpatient/outpatient), and insurance plan type (Banks et al., 2021; Groenewald et al., 2018; Groenewald 2019). Specifically, there is a positive association between pediatric patients' age and opioid prescriptions, and non-Latinx White, compared with Latinx or non-Latinx Black, patients have higher odds of receiving opioids (Banks et al., 2021; Ehwerhemuepha et al., 2021; Groenewald et al., 2018; Groenewald 2019). Additionally, prescriber setting influences opioid prescribing rates, and primary care physicians in rural areas prescribe opioids at a higher rate than do those in urban settings (Garcia et al., 2017). The health care teams' implicit and explicit decision-making process to prescribe opioids for children is complex and, thus, identifying and understanding the factors that guide those decisions is essential to advancing equitable treatment of all members in all communities.

Surprisingly little is known about how community-level factors influence opioid prescribing patterns in an inpatient pediatric setting. Given our hypothesis that pediatric patients living in more affluent neighborhoods will have greater odds of receiving an opioid prescription relative to those from less affluent neighborhoods, we define opioid prescribing patterns as a binary measure indicating whether or not an opioid analgesic was prescribed; however, in the broader literature, opioid prescribing patterns may include morphine milligram equivalents, quantity of pills prescribed, and/or days prescribed (Garcia et al., 2017; Van Winkle et al., 2020). To the best of our knowledge, there is only one publication where scholars examined the relevance of neighborhood-level characteristics to the prescribing patterns of opioid drugs to children (Dickens et al., 2022). Their findings indicate that area-level indicators, derived from residential addresses, are associated with the odds of receiving an opioid, with children living in more distressed neighborhoods being more likely to receive a prescription (Dickens et al., 2022). Their sample, however, is restricted to pediatric patients within a single trauma center in a largely rural catchment area (Dickens et al., 2022).

Here, we provide a comprehensive portrait of children's residential context by integrating community-level factors such as socioeconomic status (SES), family structure (female-headed households), and racial/ethnic composition (racial segregation) to systematically explore the variation in pediatric opioid prescribing patterns. Crucially, given that neighborhoods in which children grow up influence multiple characteristics observable by the health care team such as behavior and language, we propose that opioid prescription rates are driven by patient's *residential* environment, independent of, and beyond, known *individual*-level factors (Li et al., 2017). Also, there is evidence that adults from more affluent neighborhoods are more likely to receive an opioid prescription when presenting to emergency departments (Joynt et al., 2013). Thus, we hypothesized that pediatric patients who reside in higher socioeconomic neighborhoods will have higher odds of receiving an opioid prescription compared to those from less affluent neighborhoods.

Methods

Data Sources

Our dataset includes EMR for pediatric patients between the ages of 0–18 admitted as inpatients from 2013–2018 across a variety of care settings in Southern California who were prescribed medication to manage pain (n = 53,735). We excluded EMR for patients with cancer-associated chronic pain based on neoplasm information (n = 1,319), as well as outlier patients in the 99th percentile for length of stay (n = 529) (Donaldson et al., 2021). Patient addresses from the EMR data were geocoded and linked to the corresponding residential Census tract. As previously done, we used Census tracts to represent neighborhoods (Massey et al., 1994). Social and economic indicators were extracted from the 2014–2018 American Community Survey (ACS) data. We excluded observations unmatched to Federal Information Processing Series (FIPS) Codes (n = 7,610), those living in Census tracts with fewer than 20 children per tract (n = 32,234), and children living outside of California (n = 90), resulting in a total sample size of 11,953 children nested within 672 Census tracts or neighborhoods.

Variables

The primary outcome of interest is a dichotomous variable representing whether or not an opioid analgesic for the child was ordered while hospitalized (0 = no opioid ordered; 1= at least one opioid ordered). We included all covariates available to us from the EMR to represent child and family characteristics. Sociodemographic characteristics include: age at time of visit, sex (1 = Girl, ref.; 2 = Boy); race/ethnicity (1 = Latinx, ref.; 2 =non-Latinx White; 3 = non-Latinx Black; 4 = Asian; 5 = Other Race); and insurance type (1 = Private, ref.; 2 = Public (e.g., MediCare or MediCal)) as a proxy for SES (Kranjac et al., 2021). Other measures include: admission type (1 = Elective, ref.; 2 = Emergency; 3 = Other (i.e., urgent care or accident)); and diagnosis based on ICD9/10 codes (0 = Absence of Diagnosis; 1= Presence of Diagnosis), including bacterial and viral infection (A00-A99), diseases of the blood and blood-forming organs and disorders involving immune mechanisms (D50-D89), endocrine, nutritional and metabolic diseases (E00-E89), diseases of the circulatory system (I00-I99), nervous system diseases (G00-G99), congenital malformations, deformations and chromosomal abnormalities (Q00-Q99), diseases of the digestive system (K00-K95), diseases of the genitourinary system (N00-N99), diseases of the musculoskeletal system (M00-M99), diseases of the respiratory system (J00-J99), injury, poisoning, and certain other external consequences, ref. (S00-T88), and other diagnoses (H00-H59, L00-L99, O00-O9, P00-P96, Z00-Z99). Also, we included length of stay (Mean = 3.82; Std. Dev. = 5.95) and patient maximum pain assessed by healthcare providers throughout the patients' hospital stay using several developmentally and situationally appropriate measurement tools, including Faces, Legs, Activity, Cry, and Consolability scale, Faces Pain Scale, Numeric Rating Scale, and Neonatal Pain, Agitation and Sedation Scale (range from 0 = no pain to 10 = severe pain). Social and economic indicators of the patient's neighborhood of residence come from the 2014–2018 ACS and include: community-level education (% adults with < 12 years of education; % adults with 12 years of education; % adults with > 12 years and < 16 years of education; % adults with 16 years of education; % adults with 18 years of education; % adults with > 18 years and < 21 years of education); median community-level income; percent of female-headed households; percent receiving public assistance; percent in poverty; percent of homes in the tract that are rented; and racial/ethnic composition measured by percent of major racialized categories (% non-Latino White; % non-Latino Black; % Latinx; % Asian; % Other Race).

Statistical Analysis

First, we used a maximum-likelihood latent profile analysis (LPA) to group neighborhoods into clusters based on a range of socioeconomic indicators extracted from the ACS data (Lazaserfield & Henry 1968). We included the above-listed ACS indicators that are often used to define a child's neighborhood of residence (Jencks & Mayer 1990). Then, we estimated a 1-profile model and fit successive models with an increasing number of profiles to characterize neighborhoods. We used model fit and usefulness statistics (AIC, BIC, a-BIC, p-value based likelihood ratio tests, and entropy), as well as theoretically driven evidence, to identify the most parsimonious model. Analyses indicated that neighborhoods, given our data, are most appropriately captured by a 4-profile solution (Table 1).

Table 1

To test the influence of distinct neighborhoods on the odds of pediatric opioid prescription, we used multilevel logistic regression modeling with Stata 16.1 software (Guo & Zhao 2000; Rabe & Skrondal 2008). This technique treats level-1 patients as nested within level-2 neighborhoods and neutralizes the lack of independence of data within higher groups. Our modeling approach uses adaptive quadrature to adjust for problems that otherwise downwardly bias estimated standard errors such as different sample sizes for level-1 and level-2 units, clustering within neighborhoods, variable numbers of cases within level-2 units, and heteroscedastic error terms (Rabe & Skrondal 2008). We performed a series of conditional models. Model 1 included only the patient-level predictors (age at time of visit, sex, race/ethnicity, insurance type, admission type, diagnosis, length of stay, and patient-reported pain levels). Model 2 adds the LPA-created neighborhoods (Advantaged, ref.; Middle-Class; Working-Class; Disadvantaged) at the neighborhood level. We report odds ratios (OR) from the regressions for ease of interpretation. As a robustness check, we estimated hierarchical linear models (HLM) on the number of prescribed opioid medications as the outcome (range = 0 (none) to 11 opioids)). The substantive interpretation of the findings reported here did not change when we used a continuous measure of opioid prescription frequency (available upon request).

Results

In Figure 1, we illustrate how the four neighborhood profiles cluster across the area of study. Based on the descriptive characteristics, we assigned the following labels: Advantaged, Middle-Class, Working-Class, and Disadvantaged. The advantaged neighborhood cluster is largely concentrated in east Orange County, north-west Riverside County, and north-west San Diego County regions. As shown in Table 1, Advantaged neighborhoods have the highest median household income ($130,461), highest overall levels of education (31% of residents have at least 16 years of education), and the lowest percentage of people living in poverty (8%). The Disadvantaged communities make up the areas around north-west Orange County and central Riverside County regions and score the worst on nearly every indicator. These communities have the lowest median household income ($41,470), the lowest education levels (48% of adult residents lack a high school degree), and the highest proportion of the population in poverty (29%).

Figure 1

In Table 2, we show descriptive information for the child and family characteristics overall, and by neighborhood context. Forty five percent of children were prescribed at least one opioid during their hospital stay, with children living in Disadvantaged neighborhoods having higher frequency of prescribed opioids (50%) than do those residing in Advantaged neighborhoods (42%). The mean age for the entire sample was 7.40 years, with children in Advantaged neighborhoods being slightly older than those in other neighborhood types. In

Figure 2, we show that, although there is some clustering of children of specific race/ethnicity across neighborhoods, each racial/ethnic group is represented within each neighborhood. As displayed in Table 2, children diagnosed with digestive system issues are slightly over-represented in Disadvantaged neighborhoods (19%) compared to those residing in other neighborhoods (Advantaged: 17%; Middle-Class: 15%; Working-Class: 18%), whereas children presenting with diseases of the blood are slightly higher in Advantaged neighborhoods (17%) relative to other communities (Middle-Class: 16%; Working-Class: 15%; Disadvantaged: 10%).

Table 2 and Figure 2

Table 3 displays the results from our multilevel logistic regression models that predict the odds of opioid prescription. The random effects estimated across all models indicate that opioid prescription for children differed significantly across neighborhoods. In Model 1 we see that as children age, boys relative to girls, children with higher pain levels, those with a longer length of stay in the hospital, and children with diseases of the circulatory system, digestive system, and musculoskeletal system, relative to those with trauma, injury, poisoning, and certain other consequences of external causes, had higher odds of being prescribed opioids. On the other hand, Other race children, relative to Latinx children, as well as children admitted for an Emergency or Other reason, relative to those admitted for Elective reasons, and children diagnosed with bacterial and viral infection, endocrine, nutritional, and metabolic diseases, nervous system diseases, and respiratory issues had lower odds of opioid prescription. In Model 2, patient-level predictions largely mirror Model 1. Still, racial/ethnic variation in opioid prescribing patterns differed between the two models. Specifically, non-Latinx white children had significantly greater odds (OR = 1.21; CI: 1.00-1.48), and Other race children had significantly lower odds (OR = 0.81; CI: 0.68-0.97), of receiving opioids relative to Latinx children. Turning next to the odds ratios for the neighborhood categories, we see that there is a stepwise pattern between neighborhoods and pediatric opioid prescription such that higher levels of disadvantage are associated independently with the odds of opioid prescription. Specifically, children living in the most disadvantaged communities had 36% higher odds (OR = 1.36; CI: 1.11-1.67) of being prescribed opioids relative to children in Advantaged neighborhoods, independent of patient-level characteristics.

Table 3

Discussion

Evidence supports the fact that individual and care setting factors influence opioid dispensing rates among pediatric patients (Banks et al., 2021; Ehwerhemuepha et al., 2021; Garcia et al., 2017; Groenewald et al., 2018; Groenewald 2019; Mazer-Amirshahi et al., 2014; McCabe et al., 2017; Van Winkle et al., 2020). We hypothesized that pediatric patients who reside in higher socioeconomic neighborhoods will have higher odds of receiving an opioid prescription compared to those from less affluent neighborhoods. Specifically, given that neighborhood context influences multiple characteristics observable by the health care team, the neighborhood in which a pediatric patient resides will influence the odds of receiving an opioid prescription. In this study, we created multidimensional community profiles of patient neighborhoods by geocoding and linking EMR data to neighborhood conditions. We uncovered an ordered relationship between the child's neighborhood of residence and opioid prescribing frequency in an inpatient setting. Under the conditions of our study and after adjusting for individual-level factors, contrary to our hypothesis, we found that pediatric patients residing in the most impoverished communities have greater odds of receiving an opioid prescription. Our findings are consistent with a previously published report showing that children living in more distressed rural areas have the highest likelihood of receiving opioid medications (Dickens et al., 2022). Additionally, at the individual level, our results are in line with the aforementioned patient-level findings showing that non-Latino whites receive opioids at a higher rate than other racial/ethnic minority patients (Ehwerhemuepha et al., 2021; Groenewald et al., 2018).

It is beyond the scope of this study to explain why differences in opioid prescribing patterns exist, but we offer a few potential reasons. First, the cultural milieu of the neighborhood affects individual's observable characteristics such as language and speech patterns (Rickford et al. 2015). This is important because health care delivery is about the patient-provider communication, and SES differences influence both providing and receiving medical information (Peck & Connor 2011). Indeed, cultural differences in communication may lead to misunderstanding on both the side of the patient and the doctor, which, in turn, can impact diagnostic decision-making, clinical guidance, and involvement in treatment (Gordon et al., 2005; Zola 1966). Related, effective communication and comprehension are powerful influencers of patient compliance with, and adherence to, medical regimens (Lutfey 2005). Second, the neighborhood context, after controlling for individual and family characteristics, has negative effects on early childhood externalizing behaviors such as hyperactivity and disruptive behaviors, and this in turn may affect nurse practitioner or physician decision-making (Garland et al., 2015; Pei et al., 2022). Third, the subculture of neighborhoods affects parenting practices, and parenting styles are associated with the experience of pain in children and adolescents (Cuellar et al., 2015; Shaygan et al., 2021). Fourth, an individual's residential neighborhood influences their sense of subjective well-being that may be related to individual differences in pain perception and sensitivity (Coghill 2010). Currently, many health care organizations are carefully examining norms and practices that lead to disparities in healthcare as a function of various individual-level factors. We argue for inclusion of neighborhood context because multiple individual- and *neighborhood*-level sociodemographic factors may combine to influence the rate of opioid prescription.

Practice implications

Here, we identified the impact of unique residential contexts on pediatric opioid prescribing patterns in a predominantly Latinx sample of children. Consequently, instead of the business-as-usual prescribing practices, it is vital to focus efforts on reducing opioid prescribing variability (Hill et al., 2017). Some organizations are already taking steps to ensure equitable prescribing practices of all members in all communities (Burton et al., 2016). For example, as part of an effort to reduce deviations in opioid prescribing practices within seven emergency departments, providers at the medical centers were given provider-specific feedback on their opioid prescribing patterns, along with a grouped-mean prescribing rate of other providers within their group. This initiative significantly reduced the variability in opioid prescription practices (Burton et al., 2016). Other medical centers reduced opioid overprescription by standardizing and establishing opioid prescribing guidelines to direct provider-prescribing habits (Burton et al., 2016). Ideally, these interventions should promote nurse practitioners' and physicians' understanding of the role that patient socioeconomic characteristics play in pain assessment and management. Thus, the ultimate goal is to not only inform health care team decision-making but to address preferences and perceptions in order to ensure equitable treatment for all.

Limitations

Although we are the first to show that opioid prescribing patterns vary by children's unique residential context, our study is not without limitations. The cross-sectional nature of our data and restriction to Los Angeles and Orange Counties in Southern California limit the scope of our analyses. Similarly, our EMR data included only admitted patients, which excludes dentists, the highest volume prescribers of opioids to pediatric patients (Groenewald 2019). Also, our analysis is constrained by the limited individual- and family-level variables available for analysis in the EMR data that are primarily intended for clinical and administrative use. For example, it has been shown that pain assessment is inferior among non-English, compared with that of English, speaking families, potentially affecting pain treatment (Jimenez et al., 2014). Still, we included all existing covariates available to us in the EMR data known to associate with opioid prescribing patterns. Future studies should apply a more comprehensive set of covariates to test the reliability of our findings, and include individual- and family-level conditions known to track with pain treatment (e.g., cultural variations in pain-related caregiver behavior; parental presence at child's bedside to advocate for pain relief or voicing objections to opioids) (Finley et al., 2009; Kristjansdottir et al., 2018; Shaygan et al., 2021). Furthermore, we followed prior work and used Census tracts to represent neighborhoods (Joynt et al., 2013). Census tracts are by no means a perfect operationalization of residential contexts, but they do remain a useful spatial entity available to us in the approximation of a neighborhood (Kranjac et al., 2021). Indeed, the granularity (i.e., geographic resolution) is of utmost importance, and our using addresses instead of zip codes does provides a more robust spatial unit of analysis (Grubesic 2008). Moreover, we do not have information on whether the patient took the prescribed medications after they left the hospital, nor whether opioids were under-prescribed, accurately prescribed, or overprescribed to children from different neighborhoods. In addition, it is important to note that 1% of health care providers who prescribe opioids (e.g., physical or pain medicine and rehabilitation specialists) account for nearly half of all provided opioid doses in the United States, but we do not distinguish between the type of provider in our analysis (Kiang et al., 2020). Finally, we found that opioid prescribing patterns vary based on the residential context in which a child lives despite that reported pain levels are not significantly different among children from different neighborhoods (see, Table 2). Despite these limitations, we are one of the first to explicitly link neighborhoods to variable opioid prescribing practices among clinicians in a pediatric inpatient setting.

Conclusion

Taken together, our methodological expansion of the field is a springboard for researchers grappling with how to study the impact of social determinants on the frequency of opioid prescriptions among children and youth. Using an innovative analytical technique to characterize neighborhoods across Southern California, we show that children living in disadvantaged communities receive more opioids than do those in more advantaged spaces. Crucially, these findings mark an important opportunity to shift the industry standard and focus beyond individual factors to parse out the influence of neighborhoods on opioid dispensing practices among pediatric patients.

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Table 1. Descriptive Neighborhood-Level Characteristics by LPA-Generated Neighborhood Categories

	Advantaged		Middle-Class		Working-Class		Disadvantaged		Diff.
Socioeconomic Proportions		95% CI		95% CI		95% CI		95% CI	
Median Income (in $10K)	130.46	(128.64—133.32)	79.83	(78.86—81.36)	56.78	(56.14—57.78)	41.47	(40.67—42.72)	<.001
% Adults < 12 years Education	4.83	(4.70—5.04)	6.96	(6.41—6.97)	24.54	(24.32—25.95)	47.63	(47.28—48.96)	<.001
% Adults = 12 years Education	9.23	(9.19—9.67)	20.96	(20.62—21.44)	28.10	(27.89—28.48)	25.00	(24.69—25.49)	<.001
% Adults > 12 and < 16 years Education	21.05	(21.02—21.86)	36.73	(36.27—36.94)	28.04	(29.05—31.05)	16.30	(16.18—20.04)	<.001
% Adults = 16 years Education	36.25	(36.03—36.60)	22.06	(21.66—22.67)	12.05	(11.78—12.48)	6.30	(6.26—6.72)	<.001
% Adults = 18 years Education	18.86	(18.58—19.31)	8.25	(8.08—8.52)	4.07	(3.95—4.24)	2.23	(2.15—2.34)	<.001
% Adults > 18 and < 21 years Education	4.74	(4.59—4.97)	2.83	(2.77—2.92)	1.70	(1.65—1.78)	1.37	(1.29—1.49)	<.001
% Adults = 21 years Education	5.04	(4.92—5.23)	2.21	(2.16—2.29)	1.50	(1.44—1.60)	1.17	(1.16—1.42)	<.001
% Receiving Public Assistance	3.98	(3.87—4.16)	7.31	(7.11—7.62)	15.29	(14.96—15.82)	25.09	(24.54—26.21)	<.001
% Female-Headed Households	5.02	(4.92—5.19)	7.19	(7.05—7.42)	12.19	(11.94—12.57)	17.43	(17.01—18.10)	<.001
% of Residents in Poverty	7.84	(7.61—8.20)	10.60	(10.35—10.99)	17.96	(17.59—18.53)	29.03	(28.30—30.18)	<.001
% of Homes Renter Occupied	35.68	(34.81—37.06)	64.66	(35.72—37.67)	51.93	(51.13—53.17)	66.46	(65.43—68.09)	<.001
Racial/ Ethnic Composition									
% Non-Latinx White	67.58	(67.00—68.50)	58.39	(57.81—59.29)	31.41	(30.76—34.43)	20.11	(20.38—23.26)	<.001
% Non-Latinx Black	4.17	(4.54—5.09)	4.48	(4.17—4.95)	5.72	(5.32—5.35)	5.69	(5.26—5.37)	<.01
% Latinx	1.79	(1.52—1.22)	14.14	(13.67—14.89)	40.73	(40.43—46.77)	55.93	(50.67—56.37)	<.001
% Asian	21.89	(21.37—22.72)	14.96	(14.52—15.64)	12.82	(12.35—13.56)	7.73	(6.89—7.93)	<.001
% Other Race	4.47	(4.32—4.70)	8.22	(8.02—8.55)	9.45	(9.72—9.60)	10.58	(10.89—15.65)	<.001
Neighborhoods n =	94		198		218		162		
Children n =	1,614		2,504		3,524		4,311		

Source: Data are from Electronic Medical Records and the 2014-2018 American Community Survey

Note: Significance is evaluated using One-Way MANOVA with the neighborhood variables as the dependent variables and LPA neighborhood type as the independent variable

Table 2. Means and Standard Deviations (SD) for Independent and Dependent Variables Overall and by Neighborhood

	Overall		Advantaged		Middle-Class		Working-Class		Disadvantaged		Sig.
Dependent Variable	Mean or %	SD	Mean or %	SD	Mean or %	SD	Mean or %	SD	Mean or %	SD	
Opioids Prescribed											
0 (none)	55.13	0.50	57.74	0.49	63.46	0.48	53.69	0.50	50.31	0.50	<.001
1 or more	44.87	0.50	42.26	0.49	36.54	0.48	46.31	0.50	49.69	0.50	<.001
Independent Variables											
Sociodemographic											
Age	7.40	5.83	8.18	5.88	7.54	5.68	7.12	5.83	7.26	5.88	<.01
Sex											
Girl	46.73	0.50	41.64	0.49	49.11	0.50	45.63	0.50	48.41	0.50	
Boy	53.26	0.50	58.36	0.49	50.89	0.50	54.37	0.50	51.59	0.50	
Race/ Ethnicity											
Latinx	58.42	0.49	11.34	0.32	30.82	0.46	69.92	0.46	82.83	0.38	<.001
Non-Latinx White	13.66	0.34	30.98	0.46	26.55	0.44	7.38	0.26	4.45	0.21	<.001
Non-Latinx Black	2.82	0.17	3.10	0.17	3.99	0.20	4.68	0.21	0.54	0.07	
Asian	10.28	0.31	22.99	0.42	20.63	0.41	6.90	0.25	2.39	0.15	<.001
Other Race	14.82	0.36	31.60	0.47	18.00	0.38	11.12	0.31	9.79	0.29	<.05
Health Insurance											
Private	27.57	0.45	77.01	0.50	47.66	0.42	15.30	0.36	7.14	0.26	<.001
Public	72.43	0.45	22.99	0.50	52.34	0.42	84.70	0.36	92.86	0.26	<.001
Patient Characteristics											
Admission Type											
Elective	27.16	0.45	32.16	0.47	39.61	0.49	24.09	0.43	20.30	0.40	<.05
Emergency	38.28	0.49	31.10	0.46	30.94	0.46	40.15	0.49	43.87	0.50	<.05
Other	34.55	0.48	36.74	0.48	29.45	0.46	35.75	0.48	35.84	0.48	<.01
Diagnosis											
Bacterial and Viral Infection	11.24	0.32	9.95	0.30	10.84	0.31	11.92	0.32	11.64	0.32	
Diseases of the Blood	13.53	0.34	16.72	0.37	15.68	0.36	14.84	0.36	9.88	0.30	<.001
Endocrine and Metabolic	15.90	0.37	20.15	0.40	14.75	0.35	16.54	0.37	12.94	0.34	<.001
Circulatory System	7.08	0.26	7.21	0.26	6.75	0.25	8.03	0.27	6.38	0.24	<.05
Nervous System	14.93	0.36	18.90	0.39	16.67	0.37	14.44	0.35	12.36	0.33	<.001
Congenital and Chromosomal	13.95	0.35	15.43	0.36	13.88	0.26	12.97	0.34	14.01	0.35	
Digestive System	17.91	0.38	16.68	0.37	15.37	0.36	18.19	0.39	19.35	0.40	<.01
Genitourinary System	6.41	0.25	4.96	0.22	7.06	0.25	6.56	0.25	6.91	0.25	<.01
Musculoskeletal System	7.19	0.26	6.73	0.25	7.25	0.26	8.37	0.28	6.52	0.25	<.05
Respiratory System	19.05	0.39	18.37	0.39	17.84	0.38	20.15	0.40	19.09	0.39	
Trauma, Injury, Poisoning	8.78	0.28	6.20	0.24	9.79	0.30	9.22	0.29	9.58	0.29	<.001
Other Diagnoses	35.00	0.48	32.76	0.47	38.85	0.49	34.62	0.48	34.93	0.48	<.01
Length of Stay	3.82	5.95	3.66	5.62	3.74	6.30	3.92	5.99	3.85	5.84	
Pain-Level	4.30	3.36	4.06	3.36	4.14	3.32	4.43	3.42	4.37	3.33	

Source: Data are from 2013-2018 Electronic Medical Records and the 2014-2018 ACS; Note: Asterisks indicate sig evaluated using two-tailed indep. means t-tests

Table 3. Multilevel Logistic Regression Models Predicting Pediatric Opioid Prescription; N = 11, 953 in 672 Census Tracts

	Model 1		Model 2	
	OR	95% CI	OR	95% CI
Intercept	0.16***	0.12—0.20	0.14***	0.11—0.18
Patient-Level				
Sociodemographic				
Age	1.06***	1.05—1.07	1.06***	1.05—1.07
Sex (Girl, ref)				
Boy	1.16**	1.03—1.30	1.16**	1.04—1.31
Race/ Ethnicity (Latinx, ref)				
Non-Latinx White	1.13	0.94—1.37	1.21*	1.00—1.48
Non-Latinx Black	1.15	0.78—1.69	1.23	0.83—1.81
Asian	0.92	0.65—1.03	0.86	0.68—1.08
Other Race	0.78**	0.66—0.93	0.81*	0.68—0.97
Patient Characteristics				
Health Insurance (Private Provider, ref)				
Public Provider	1.02	0.88—1.18	0.96	0.83—1.13
Admission Type (Elective, ref)				
Emergency	0.37***	0.32—0.44	0.37***	0.31—0.43
Other	0.55***	0.46—0.66	0.54***	0.45—0.64
Length of Stay	1.08***	1.06—1.09	1.08***	1.06—1.09
Pain Levels	1.48***	1.45—1.51	1.48***	1.45—1.51
Diagnosis (Trauma, Injury, Poisoning, ref)				
Bacterial and Viral Infection	0.58***	0.47—0.70	0.58***	0.48—0.70
Diseases of the Blood	0.86	0.71—1.05	0.86	0.71—1.05
Endocrine and Metabolic	0.55***	0.45—0.66	0.56***	0.46—0.67
Circulatory System	1.67***	1.32—2.11	1.66***	1.32—2.10
Nervous System	0.69***	0.58—0.83	0.70***	0.58—0.84
Congenital and Chromosomal	0.97	0.81—1.17	0.97	0.80—1.17
Digestive System	2.59***	2.22—3.03	2.59***	2.22—3.02
Genitourinary System	0.97	0.77—1.23	0.97	0.77—1.23
Musculoskeletal System	1.30*	1.03—1.64	1.31*	1.04—1.65
Respiratory System	0.48***	0.41—0.57	0.48***	0.41—0.57
Other	0.96	0.83—1.10	0.95	0.82—1.10
Neighborhood-Level				
Neighborhood (Advantaged, ref)				
Middle-Class			1.14	0.89—1.47
Working-Class			1.17	0.96—1.44
Disadvantaged			1.36**	1.11—1.67
Random Effects				
Tract	0.15***	0.09—0.25	0.14***	0.08—0.24

Source: Data are from 2013-2018 Electronic Medical Records and the 2014-2018 ACS
****p<0.001, **p<0.01, *p<0.05*

Figure 1. Neighborhood profiles by census tracts, Southern California.

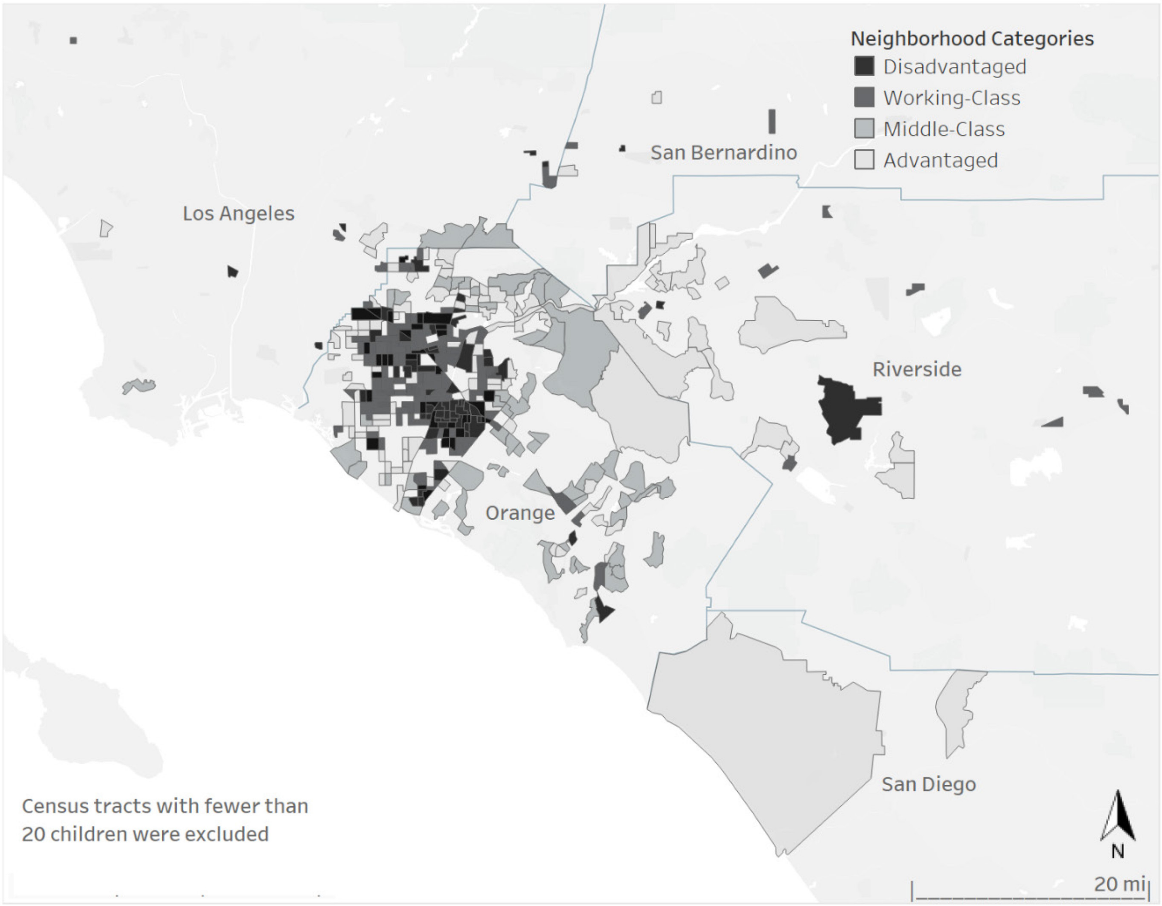
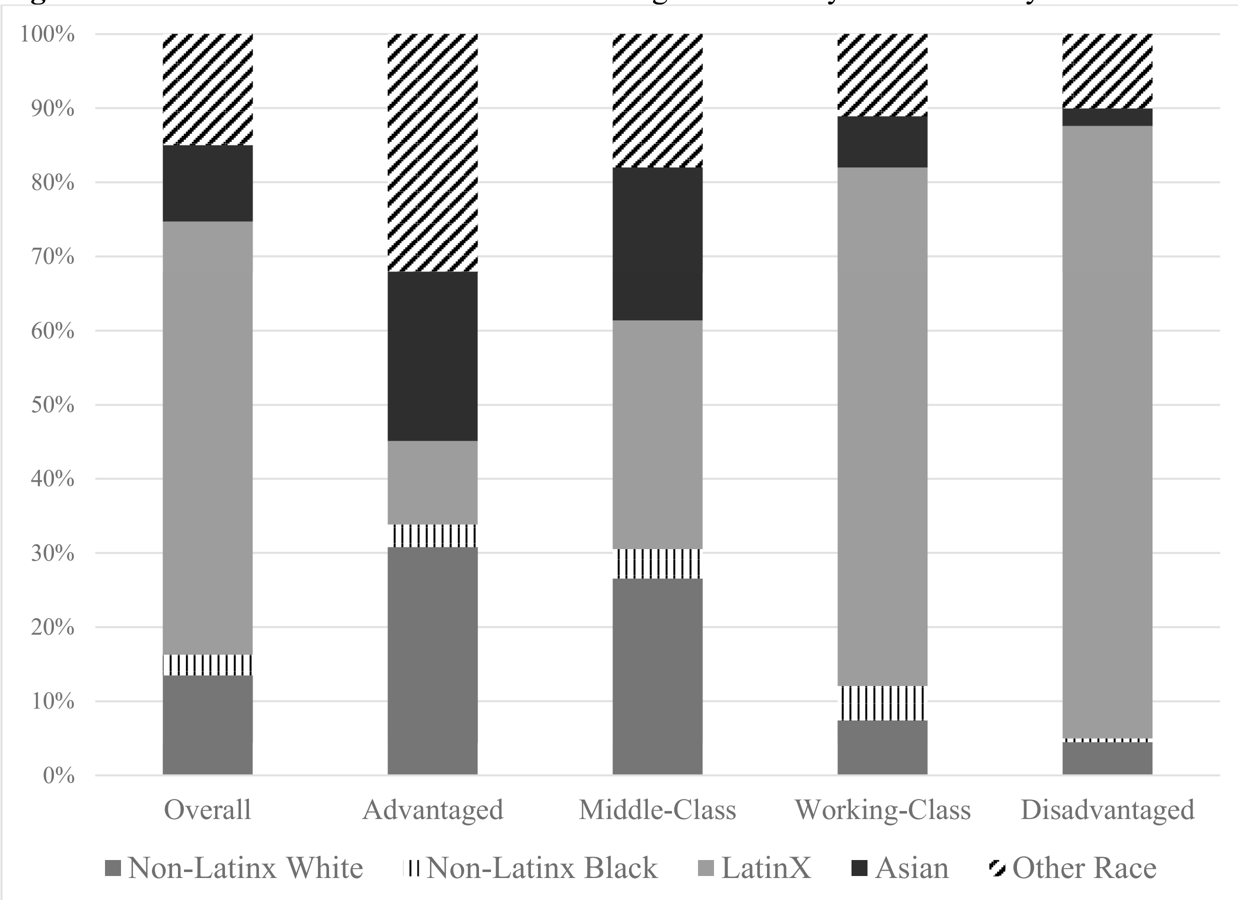


Figure 2. Distribution of Children across LPA Neighborhoods by Race/Ethnicity



Source: Data are from Electronic Medical Records and the 2014-2018 American Community Survey