Table. Engagement With Federally Backed Helplines 1 Week After a Celebrity Overdose and Suicide

	Key Words, No. of Mentions or Searches[a]					
	Demi Lovato Overdose			Anthony Bourdain Suicide		
Source	*Lovato*	*Opioid* or *Heroin*	*800-662-HELP*[b]	*Bourdain*	*Suicide*[c]	*800-273-TALK*[b]
Google News	42 500	25 300	216	22 400	120 000	4940
Twitter	972 500	342 200	258	2 205 300	2 117 000	20 900
Google search	14 700 000	1 200 000	8000	18 900 000	3 827 000	29 000

[a] Counts reflect weekly volumes for news stories archived on the study sources 1 week after Lovato's overdose (July 24, 2018) and Bourdain's suicide (June 8, 2018).

[b] Raw Google search volumes were estimated by monitoring queries per 10 million, with the denominator inferred from comScore summaries. Searches for *help* or *helpline* were also included to capture those searching for these national hotlines.

[c] Excludes matching content that also included *blast*, *bomber*, *doors*, or *squad*.

method searches, such as *I want to kill myself*. Likewise, social media companies have implemented strategies to reach suicidal users who need help.[5] Similar efforts could be applied to drug addiction, with industry prioritizing 800-662-HELP within their platforms when their users seek out help.

The managers of 800-662-HELP could use search engine and smartphone-based conversational agent (ie, Siri) optimization to fill existing awareness gaps without relying on media companies themselves.[6] Moreover, replicating mass media campaigns, such as how Tips From Former Smokers promotes the smoker's helpline, might also insert 800-662-HELP into the national conversation, thereby engendering broader free media coverage. The result of these changes will mean more of those who need help know of 800-662-HELP, and tragedies, like that besetting Lovato, could have a positive effect on public health.

John W. Ayers, PhD, MA
Alicia L. Nobles, PhD, MS
Mark Dredze, PhD

Author Affiliations: Division of Infectious Diseases and Global Public Health, Department of Medicine, University of California, San Diego, La Jolla (Ayers, Nobles); Department of Computer Science, The Johns Hopkins University, Baltimore, Maryland (Dredze).

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Corresponding Author: John W. Ayers, PhD, MA, Division of Infectious Diseases and Global Public Health, Department of Medicine, University of California, San Diego, 9500 Gilman Dr, CRSF Room 333, La Jolla, CA 92093 (ayers.john.w@gmail.com).

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Place-Based Inequity in Smoking Prevalence in the Largest Cities in the United States

Achieving universal health and well-being for all Americans is the ideal goal for US public health efforts, but inequities in chronic disease and life expectancy present a persistent challenge, particularly in large cities.[1] In 2016, the Robert Wood Johnson Foundation and the US Centers for Disease Control and Prevention launched the 500 Cities Project, providing small-area estimates of modifiable risk factors for chronic disease in the 500 largest US cities.[2] To guide prevention efforts, we used these data to characterize inequities in cigarette smoking both between and within cities and in relation to sociodemographic factors and chronic diseases.

Supplemental content

Methods | The 500 Cities Project provides model-estimated health indicators at the census-tract level from the 2014 Behavioral Risk Factor Surveillance Survey.[2] A census tract is generally smaller than a city, larger than a block group, and a fairly permanent subdivision of a county. Our analysis used the prevalence of adult (≥18 years) self-reported current smoking, asthma, chronic obstructive pulmonary disease (COPD), and coronary heart disease (CHD). Complete data from the 500 Cities Project were available for 27 204 tracts. We combined the 500 Cities Project estimates with tract-level sociodemographic data from the American Community Survey (2012-2016) and counts of likely tobacco retailers from 10 North American Industrial Classification System codes in the National Establishment Time Series Data for 2012 (120 470 tobacco retailers in the 27 204 tracts).[3]

We used linear mixed models to characterize smoking prevalence inequities within and between cities; assess tract-level

smoking prevalence as a function of tract-level sociodemographic characteristics and tobacco retailer counts; and assess tract-level asthma, COPD, and CHD prevalence as a function of tract-level smoking prevalence. We also computed Gini coefficients to quantify the dispersion of smoking prevalence between census tracts within each of the 500 cities, where 0 = perfect equality and 1 = maximal inequality.[4] Data sources and analytical methods are further detailed in the Supplement.

Results | Smoking prevalence inequities were greater between tracts within cities (56.1% of the total variation) than between cities (43.9% of the total variation) (**Table**). Tracts with higher smoking prevalence had more tobacco retailers (5-store increase, β = 0.11; 95% CI, 0.07-0.16; *P* < .001), lower median household income ($10 000 increase, β = −0.92; 95% CI, −0.94 to −0.90; *P* < .001), and a smaller percentage of non-Hispanic white residents (10% increase, β = −0.84; 95% CI, −0.86 to −0.82; *P* < .001).

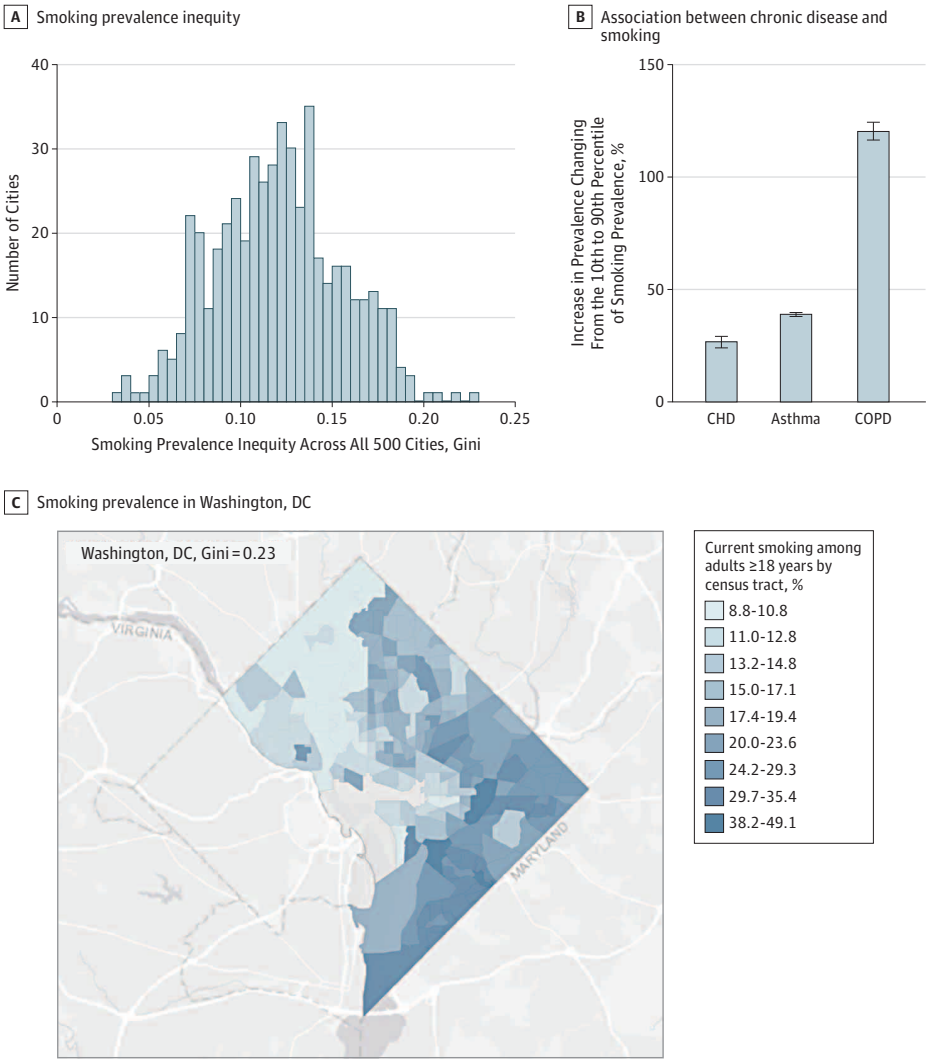
Although all cities had some smoking prevalence inequity (**Figure**, A) (Gini coefficients ≥0.03), inequity was greatest in Washington, DC (Gini = 0.23); Atlanta, Georgia (Gini = 0.22); Fort Lauderdale, Florida (Gini = 0.21); and Miami, Florida (Gini = 0.20). Figure, C illustrates smoking prevalence in the city with the greatest inequity, Washington, DC.

Table. Fixed Effects and Random Effects Resulting From the Linear Mixed Models for Smoking Prevalence Among 27 204 Census Tracts in the 500 Cities Project[a]

Fixed Effect	β (95% CI)	*P* Value
Intercept	27.89 (27.54 to 28.24)	<.001
No. of tobacco retailers (5-store increase)	0.11 (0.07 to 0.16)	<.001
Median household income ($10 000 increase)	−0.92 (−0.94 to −0.90)	<.001
Percent non-Hispanic white population (10-percentage-point increase)	−0.84 (−0.86 to −0.82)	<.001
Random effects (null model)	Variance (95% CI)	
Between-city	18.73 (16.46 to 21.33)	<.001
Residual (within-city)	23.97 (23.57 to 24.38)	

[a] Listwise deletion was used for 125 tracts that were missing information on household income. All models with fixed effects simultaneously adjust for the listed fixed effects and also for total population size.

Figure. Smoking Prevalence Inequities and Their Association With Inequities in Chronic Diseases



A, All cities have at least some inequity (Gini coefficient ≥0.03) and 4 cities (Washington, DC; Atlanta, Georgia; Fort Lauderdale, Florida; and Miami, Florida) have particularly high inequity (Gini ≥0.20). B, The prevalence of current self-reported asthma, chronic obstructive pulmonary disease (COPD), and coronary heart disease (CHD) is higher in tracts with higher prevalence of current smoking. Estimates shown in Figure 1B result from multivariable linear mixed models that adjust for percent non-Hispanic white population, median household income, total population size, and a random effect for city. We calculated the expected percent increase in prevalence of each chronic disease of changing from the 10th to 90th percentile of smoking prevalence (from 10.7% to 27.6%) and the corresponding 95% confidence intervals using these multivariable linear mixed models and by using 1000 draws from the multivariate normal distribution with the mean equal to the maximum likelihood point estimate and the variance equal to the coefficient covariance matrix. C, Differences in tract-level smoking prevalence for the city with the greatest inequity in smoking prevalence: Washington, DC (Gini = 0.23). The color in the image uses Jenks natural breaks (9 classes) based on the data for the Washington, DC, census tracts. One Washington, DC, census tract had insufficient data to make a smoking prevalence estimate and is illustrated in gray. Data sources and analytical methods are further detailed in the supplementary appendix.

At the tract level, higher smoking prevalence was associated with higher prevalence of asthma, COPD, and CHD (Figure, B). For instance, a change from the 10th to the 90th percentile of smoking prevalence (from 10.7% to 27.6%) was associated with a 38.9% (95% CI, 38.1%-39.5%) increase in the prevalence of asthma, a 120.2% (95% CI, 116.6%-124.0%) increase in the prevalence of COPD, and a 26.6% (95% CI, 24.5%-29.0%) increase in the prevalence of CHD.

Discussion | Smoking prevalence was unevenly distributed both within and between America's largest cities, and was associated with inequities in income, race, exposure to tobacco retailers, and smoking-related diseases. Strengthening existing tobacco control interventions, such as raising excise taxes and implementing cessation programs targeted to resource-poor communities, may aid in counteracting these inequities in smoking.[5] In addition, novel policies that restrict the retail environment (eg, by limiting the quantity, location, and type of tobacco retailers) show promise for reducing the unequal distribution of tobacco retailers and warrant further investigation.[6]

Eric C. Leas, PhD, MPH
Nina C. Schleicher, PhD
Judith J. Prochaska, PhD, MPH
Lisa Henriksen, PhD

Author Affiliations: Stanford Prevention Research Center, Stanford University School of Medicine, Palo Alto, California.

Corresponding Author: Eric C. Leas, PhD, MPH, Stanford Prevention Research Center, Stanford University School of Medicine, 3300 Hillview Rd, Ste 114, Palo Alto, CA 94304-1334 (ecleas@stanford.edu).

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Study concept and design: Leas, Schleicher, Henriksen.
Acquisition, analysis, or interpretation of data: All authors.
Drafting of the manuscript: Leas, Henriksen.
Critical revision of the manuscript for important intellectual content: All authors.
Statistical analysis: Leas, Schleicher.
Obtained funding: Henriksen.
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Study supervision: Prochaska, Henriksen.

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Utilization of Long-Acting Reversible Contraceptives in the United States After vs Before the 2016 US Presidential Election

Soon after the US presidential election on November 8, 2016, media and industry reports described an increase in utilization of long-acting reversible contraceptive (LARC) methods (intrauterine devices and implants).[1] Proposed reasons included women's concerns about contraceptive access should the Patient Protection and Affordable Care Act (ACA) be repealed during the Trump Administration. These reports, however, were descriptive and did not control for seasonal or secular trends. Using data from a large sample of commercially insured women, we sought to assess whether there was an increase in LARC utilization among commercially insured women during the 30 days after the election, compared with the 30 days before the election and the same period in 2015.

+ Supplemental content

Methods | Using the IBM/Truven MarketScan Analytics Commercial Claims and Encounters Database, we studied women aged 18 to 45 years enrolled in commercial insurance during the 30 business days before and after November 8 in 2015 or 2016 who had at least 12 months of continuous enrollment. We used billing codes (eTable in the Supplement) to calculate daily LARC insertion rates during the 30 business days before (inclusive of November 8) and 30 days after November 8 in 2015 and 2016. To account for secular trends, we estimated changes in daily LARC insertions using a difference-in-differences generalized linear model with a Poisson distribution and log link function that compared the change in probability of LARC insertion during the 30 business days before vs after November 8, 2016, with the change in the comparable period in 2015. With person-day as the unit of analysis, we adjusted for age group, region, relationship to the insured individual, and plan type (**Table**) and accounted for clustering by individuals (because individuals contributed information for multiple time points). Wald tests were used to calculate the P values. We considered a 2-sided $P < .05$ to indicate statistical significance. The Harvard Medical School Office of Human Research Administration exempted the study from human subject review; therefore, patient consent was not required. All data were deidentified.

Results | Among 3 449 455 women in 2015 (mean [SD] age, 31.8 [8.3] years) and 3 253 703 women in 2016 (mean [SD] age, 31.8 [8.4] years), demographic and health plan characteristics were similar (Table). In 2015, the mean adjusted