

RACIALIZED EMPATHY

Racialized Empathy for the Drug Addicted: How Do We Respond?

By Champe Barton

I. Introduction

In recent years, American legislators, journalists, and public intellectuals have mustered an outpouring of empathy for our country's floundering white working class. Despite overwhelming evidence¹ to the contrary, congressmen and news broadcasters alike insist that liberal disdain for working whites — “rednecks” and “hillbillies” gripped by economic angst — served Donald Trump the 2016 election on a silver platter. How else should a citizen react, they ask, when scorned and neglected by America’s elite?

Unfortunately, we seldom apply this logic to the plight of Black America. In the face of vast, historical disregard for black Americans’ struggle, we neither expect that they succumb to the irrational allure of orcish reality-television stars nor strain to understand the frustration that motivates their protests and riots.

Writer Ta-Nehisi Coates puts it well:

“Black workers suffer because it was and is our lot. But when white workers suffer, something in nature has gone awry. And so an opioid epidemic among mostly white people is greeted with calls for compassion and treatment, as all epidemics should be, while a crack epidemic among mostly black people is greeted with scorn and mandatory minimums.”

This disparate reaction to the crack and opioid epidemics has arguably provided the clearest example of our racialized empathy, and many have taken notice. The Chicago Tribune², The New York Times³, The Atlantic⁴, Vox⁵, The Sun-Sentinel⁶,

¹ *The Mythology of Trump’s Working Class Support*, FiveThirtyEight

² *Race, the Crack Epidemic, and the Effect on Today’s Opioid Crisis*, Chicago

² *Race, the Crack Epidemic, and the Effect on Today’s Opioid Crisis*, Chicago Tribune

³ *When Addiction Has a White Face*, The New York Times

and others have all published articles pointing to the inequity in our respective responses.

But what evidentiary basis do these writers have for their claim that the opioid epidemic's predominantly white demographic has softened our response to addiction? Is their collective assumption that we responded differently to each epidemic even grounded? And if so, how can they ascribe the cause to race and not other variables like scientific awareness or increased social connectivity? This analysis aims to provide that evidentiary basis or lack thereof, to tease these causes apart and investigate whether the racial profile of the opioid epidemic really did cause a softening in America's public response to addiction.

II. Sample

This study analyzed 557 New York Times articles from fourteen peak years of the crack (1985-1998) and opioid (2004-2017) epidemics and compared word usage during each period with a series of independent Welch Two Sample t-tests, which account for unequal variances. A second analysis conducted with 28 years (1982, 1985, 1988, 1990-2014) of articles regressed the resulting word usage data on racial demographic data for crack and heroin use in each year, a measure of scientific understanding of addiction in each year, and a measure of technological progress for each year.

III. Word-Search Analysis

⁴ *What the 'Crack Baby' Panic Tells Us About the Opioid Epidemic*, The Atlantic

⁵ *When a Drug Epidemic's Victims are White*, Vox

⁶ *White Opioid Addiction Raises Sympathy Not Found During Crack Epidemic*, The Sun-Sentinel

I analyzed 25 pages of NYT article search results (according to a specified search term) per year for 14 years from the NYT's article archive, using the search terms "crack epidemic" and "opioid epidemic". I then counted the frequency of usage of a series of arbitrarily defined 'apathetic' and 'empathetic' words, apathetic words referring to those that frame addiction predominantly as a criminal justice problem; empathetic words referring to those that frame it predominantly as a public health problem.

IV. Apathetic Words

Apathetic words were chosen based on several characteristics: first, I consulted a National Alliance of Advocates for Buprenorphine Treatment⁷ memo regarding word usage and addiction. From that list, I chose words I considered common enough to appear in newspaper articles more than a handful of times (e.g. "wellbriety," a word they suggest people use, is much less likely to appear consistently in articles spanning a forty-year period than "habit"). I then decided on an arbitrary list of additional words based 1) on how well I felt they characterized the problem as the responsibility of the criminal justice system, and 2) on how frequently the word appeared in a series of test-searches. For the t-test, I decided on nine words: "prison", "crime", "criminal", "police", "justice", "arrest", "threat", "violence", and "habit". None were removed from the analysis.

V. Empathetic Words

Empathetic words were chosen using all the same criteria as apathetic words, except I selected them based on how well I felt they pinned responsibility

⁷ Substance Use Disorders: A Guide to the Use of Language, National Alliance of Advocates for Buprenorphine Treatment

for addressing the epidemic on the public health system, rather than the criminal justice system. Again, I decided on nine words for the t-test: "treatment", "disease", "sick", "health", "survivor", "insurance", "patient", "overdose", and "misuse." "Survivor" was removed from the t-test analysis because it appeared zero times in each search. Based on a NYT daily article request limit, I was unable to re-run the t-test with another substitute word.

VI. Dependent Variables

Media Response

Media response was analyzed using 30 archived New York Times⁸ articles from the each year in the 28-year period listed above. The variable in the regression used a ratio of empathetic words to apathetic words used in the 30 most relevant articles according to searches for "cocaine" and "heroin" in each focus year.

This approach has the advantage of accounting for articles that take into account both criminal justice and public health responses, but has the disadvantage of potentially missing or misinterpreting information from each piece (e.g. an article that reads, "we shouldn't look at drug use as a bad habit or a threat — this isn't a criminal justice problem; it's a public health problem" would register more apathetic than empathetic words, despite framing the problem in a more empathetic light).

Legislative Response

⁸ The New York Times Article Archive, The New York Times

Data for the U.S. legislative response to addiction epidemics in the given years can be found on the Congress.gov⁹ website using their Congressional bill tracker. The database contains data on every bill proposed and the policy areas each covers, and a straight tally was taken of those proposed in ‘criminal justice’ and ‘public health’ subject areas that also contain the keyword “drug abuse”, which surfaced more bills than “substance abuse,” “addiction,” and “drug addiction.” I then compared the number of criminal justice-related bills proposed vs. the number of health-related bills proposed in each year to generate a rate that would give a better idea of Congressional focus than raw tallies would.

VII. Independent Variables

Racial Profile

The racial profile of the crack and opioid epidemics may be responsible for the apparently dramatic shift in response from the former to the latter. Racism can be slippery to quantify empirically (one reason: white families collectively share more power than black families in the U.S., so when the children of white families die from opioid overdoses, parents might respond more forcefully and empathetically than when watching the children of unknown black families die. Is this racism or basic psychology?), but determining whether or not race played a role at all in our response shift is a necessary first step in any attempt at doing so.

This racial demographic information can be quantified by several different metrics. Drug- and demographic-specific arrest data, overdose data, self-reported use data, and emergency room data all provide slightly different angles to approach such an analysis, and could yield slightly different results (e.g. heroin

⁹ Congressional Bill Search, U.S. Congress

users may overdose more often than crack users, skewing rates of heroin overdose relative to cocaine overdose). However, since drug- and demographic-specific arrest, overdose, and emergency room data do not exist in any one unified database for the years in question, I focused instead on self-reported use data only.

To do so, I analyzed data provided by the National Institute's on Drug Abuse survey, the National Survey on Drug Use and Health (NSDUH)¹⁰, which until 2001 was called the National Household Survey on Drug Abuse (NHSDA). A NIDA representative administers this self-reported survey in person, and its sample is randomized to remain representative. After examining the data in Microsoft Excel, yearly population demographic estimates would be inaccurate given NIDA's response rates. As such, I used a ratio of the rate of heroin + crack/cocaine use in black respondents to the rate of the same in white respondents. A lower number would signify higher rates of heroin and crack/cocaine use in the white community, while a larger number would signify greater use in the black community.

Scientific Awareness

Scientific understanding of addiction as a disease has developed over time, and could potentially change the way we respond to addiction epidemics. The same way ancient peoples punished their mentally unwell for demonic possession before their conception of mental health, we may have punished the drug addicted for a moral failing before we fully understood their condition as

¹⁰ Substance Abuse and Mental Health Services Administration

neurochemical. Thus, scientific awareness of addiction represents an important confounding variable to consider.

This awareness was tracked using the rate of scientific journal articles containing the phrase “disease of addiction” in Google Scholar searches for each of my focus years.

Technological Progress

Technological advancement can both increase media awareness and sympathy for a problem, and can reduce violence by lessening the number of “surprise” interactions that involve dealers, both of which can indirectly result in a more empathetic public response. “Surprise” interactions refer to hostile interactions that occur in less connected communities as a result of unexpected encounters — in plain terms, the interactions between drug dealers and addicts/other dealers that the advent of technology like Facebook and iPhones could have eliminated by way of shortening the amount of time it takes to send a warning, increasing awareness of activity in communities, enhancing police ability to respond preemptively, etc.

Technological progress is traditionally measured using total factor productivity (TFP), “the portion of output not explained by the amount of inputs used in production.”¹¹ It measures how efficiently inputs are utilized in production, and thus serves as a useful proxy for technological progress. The

¹¹ Total Factor Productivity, New York University and NBER

Federal Reserve Bank of St. Louis¹² keeps meticulous annual TFP data publicly available.

VIII. T-Tests

A total of 17 t-tests were run, each comparing the average number of times an individual word in the list was used per article between the two epidemics. Two additional tests were run to compare the average apathetic and empathetic word totals per article between the two epidemics as well. The results, before correction for multiple comparisons, were as follows:

EMPATHETIC WORDS

	t	df	p-value	95% C.I.	more frequent in:	crack mean	opioid mean
TREATMENT	-3.4922	264.6	0.0003909	(-1.5667, -0.4573)	opioid	0.8808864	1.8928571
HEALTH	-4.1046	272.74	0.0000053	(-2.1901, -0.7704)	opioid	1.249307	2.729592
PATIENT	-2.5949	224.62	0.01008	(-0.6942, -0.0949)	opioid	0.1717452	0.5663265
SICK	1.0608	442.88	0.2894	(-0.0288, 0.0965)	no sig. difference	0.10526316	0.07142857
INSURANCE	-2.7701	280.66	0.005977	(-0.7044, -0.1192)	opioid	0.1800554	0.5918367
MISUSE	-2.7697	198.73	0.006143	(-0.1350, -0.0227)	opioid	0.002770083	0.081623653
OVERDOSE	-7.5714	197.99	0.0000000	(-1.1993, -0.7036)	opioid	0.0332410	0.9846939
DISEASE	2.1832	513.11	0.02947	(0.0208, 0.3948)	crack	0.4986150	0.2908163
SURVIVOR	-	-	-	-	-	-	-
TALLY	-5.7474	262.47	0.0000000	(-5.4802, -2.6834)	opioid	3.127424	7.209184

APATHETIC WORDS

	t	df	p-value	95% C.I.	more frequent in:	crack mean	opioid mean
PRISON	3.4157	545.62	0.0006835	(0.1027, 0.3808)	crack	0.3795014	0.1377551
CRIME	6.8895	415.73	0.0000000	(0.8531, 1.5342)	crack	1.3518006	0.1581633
CRIMINAL	2.3755	481.17	0.01791	(0.0307, 0.3239)	crack	0.3711911	0.1938776
JUSTICE	1.2297	456.59	0.2194	(-0.0629, 0.2732)	no sig. difference	0.3296399	0.2244898
POLICE	3.9748	430.78	0.0000082	(0.7080, 2.0930)	crack	2.451524	1.051020
ARREST	3.8284	552.91	0.0001437	(0.0682, 0.2120)	crack	0.19113573	0.05102041
THREAT	0.88135	400.26	0.3787	(-0.0403, 0.1060)	no sig. difference	0.12465374	0.09183673
VIOLENCE	5.363	533.59	0.0000000	(0.2478, 0.5343)	crack	0.4930748	0.1020408
HABIT	1.6419	542.67	0.1012	(-0.0693, 0.0737)	no sig. difference	0.06925208	0.03571429
TALLY	6.1655	478.99	0.0000000	(2.5096, 4.8574)	crack	5.836565	2.153061

¹² Total Factor Productivity at Constant National Prices for United States, St. Louis Fed

To reject the null in this case is to reject the hypothesis that — in each individual comparison — no difference exists between the average frequency of the word's use per article in the search. The alternative hypothesis, then, supposes that there is such a difference *word to word*. As a result, the individual word comparisons only serve as instruction to future researchers deciding on words to include or exclude in future analyses. The true points of interest here lie in the average tally comparisons, which provide a more holistic view of apathetic and empathetic word usage in either epidemic.

In total, thirteen of the seventeen words, along with both word totals, were used significantly differently based on the time period of their use. Only three apathetic words (“justice,” “threat,” and “habit”) and one empathetic word (“sick”) were used without significant difference.

However, correcting for multiple comparisons using the Bonferroni method revealed five additional words whose significance I evidently found by chance: “patient,” “misuse,” “insurance,” “disease,” and “criminal.” In total, this left significant differences among three out of eight empathetic words, four out of eight apathetic words, and both word totals.

These results suggest a relatively stark contrast in the language use surrounding the crack and opioid epidemics, namely that we focused more heavily on the criminal justice response to addiction during the crack epidemic, and more heavily on the public health response to addiction during the (ongoing) opioid epidemic.

IX. Regressions

With two dependent variables, I essentially ran two separate regressions with the same independent variables, swapping only the dependent variable of interest. Due to a poverty of annual data on national drug use (and thus a number of observations below even the most basic $n = 30$ threshold), though, this regression provides no reliable results. Regardless, it serves as a suggestion of possible future avenues for researchers to explore, and as caution against time-consuming mistakes that may obscure very real effects or worse, provide evidence of effects that do not exist.

The results of my regression on media response (variable name “emp_rate” for the rate of empathetic/apathetic words used) were as follows:

drug_use

Racial demographics of drug use were an insignificant predictor of journalistic empathy for the drug addicted in the New York Times. On face value, this would be interpreted as evidence that the race of the drug addicted does not affect the media’s response to addiction. However, given the limitations of this analysis, that would be an immature interpretation. The primary issue here lies with my dependent variable. Arbitrarily selecting proxy words for empathetic and apathetic responses necessitates a trial and error process I haven’t had the time — or the data-request limit license — to work through. Fairly decisively, apathetic words beat out empathetic words in NYT article content for the years in question, for understandable reasons: both cocaine and heroin are illegal drugs. Using them constitutes a crime, meaning that in nearly every year, “crime” tallied up a bulk of the interval’s apathetic totals, ultimately evening out my data over the

thirty years in question. In future iterations, researchers should consider removing this term to get a more specific gauge of our language-use surrounding addiction.

I also didn't control for the frequency of each of these words in the English language. In the iterations of this analysis to come, future researchers should find some metric for doing so in order to get an accurate sense of when a word is being used at higher-than-typical rates.

Additionally, the drug use data available to me came with some caveats regarding trend analysis. Methodology for the study changed twice over the years in question (once between 1985 and '88, and once in 2002). Although I partially succeeded in negating this methodological variation by using ratios rather than raw figures, the changes injected some inconsistency into an already-small data set. With so few observations, my analysis was especially vulnerable to these inconsistencies.

Lastly, my data set was small. Without another accurate annually reported drug-use demographic database, I only have data from 28 years, not even enough to satisfy the basic $n=30$ significance threshold.

sci_awareness

Scientific awareness also proved an insignificant predictor of media response, but this makes sense given the above dependent variable issue. Sharper media data may correlate higher with our increasing scientific awareness.

tech_progress

Just like scientific awareness, technological progress likely suffered from the same dependent-variable problems, and may also contain an interaction

effect with media response that obscures any effect it exerts specifically (e.g. increasing technological advancement increases our capacity to report stories and the quickness with which we're able to report them).

The results of my regression on legislative response (variable name bill_count for the rate of criminal justice bills over public health bills proposed related to drug abuse each year) are as follows:

drug_use

Again, drug used proved an insignificant predictor, this time for our country's legislative response to drug addiction. Also again, however, this insignificance may result more from inadequacies in the dependent variable data than in the independent variable data. The primary reason for this is that a count of bills proposed in a given year mentioning a certain search term pays no mind 1) to whether or not a bill becomes law or 2) to the content of the bills in question. For example, mandatory minimum sentencing laws contained in the Anti-Drug Abuse Act of 1986 may have had the single greatest race-related and race-motivated impact of any law since Jim Crow. But according to my analysis, the passage of such draconian legislation registers only as a single tally, canceled out by a health-related bill that simply mentions the risk of opioid abuse from the prescription of pain meds.

Alternatively, it's also possible that it's media response — not actual racial demographics — that most significantly impacts legislation proposed. Future research should consider some way of accounting for the interaction between media and legislative responses if it aims to address underlying endogeneity problems.

sci_awareness

Scientific awareness proved a significant predictor of legislative response at the 95% confidence level with a p-value of 0.0187. The two variables are inversely correlated, so an increase in scientific awareness decreases the bill_count variable (meaning it increases the number of health-related bills proposed to address drug abuse relative to the number of criminal-justice related bills proposed). This confirmed my hypothesis: Congress hears testimony from scientific experts every day; when important information regarding costly public health crises turns up in laboratory experiments, Congressmembers are some of the first people to hear it. For this reason, it makes sense that they would adjust their policy-making accordingly.

However, again this dependent variable fails to take into account the quality of a proposed bill. Just because Congress proposes more health-related bills in response to scientific evidence doesn't mean they put their full effort behind those proposals; a single bill like the Anti-Drug Abuse Act of 1986 carries consequences for generations of black and brown Americans, and arguably reflects the priorities of government better than does the quantity of health-related bills that mention "drug abuse."

tech_progress

Technological progress again proved insignificant — this is likely because whatever effect it has on drug-related crime is so indirect as to not register at the levels of media or government response. It should be removed in later analyses.

REGRESSIONS

	media	legislative
SCI_AWARENESS	-0.01246 (-0.847)	-0.012177* (-2.523)
DRUG_USE	1.04135 (0.567)	-0.074764 (-0.124)
TECH_PROGRESS	3.86392 (0.717)	0.452945 (0.256)
ADJ. R-SQUARED	-0.08515	0.2265

t-values in parentheses

* = significant at 95% confidence level

X. Summary Statistics

In order to avoid presenting 36 separate summary statistic sets for each word used during each epidemic, I only include the total apathetic and empathetic word tally summary statistics. These variables essentially contain a rougher version of the data contained in the 36 single-word summary statistics, do not take multiple pages to display, and provide a clearer, more focused lens through which to examine changes in word use. Additionally, it is these broader umbrella variables that provide the most useful information in such an analysis. Single-word t-tests simply offer instruction for analyses.

SUMMARY STATS

	min	1st Q	med	mean	3rd Q	max
TECH_PROGRESS	0.7390	0.8482	0.9230	0.9125	0.9852	1.0410
SCI_AWARENESS	5.141	14.961	19.919	24.336	30.327	72.285
DRUG_USE	0.3710	0.4662	0.4975	0.6106	0.7272	0.9680
MEDIA_RESP	0.3040	0.5357	0.6755	0.7519	0.9715	1.2630
LEG_RESP	0.2880	0.7485	1.3475	1.3940	1.7650	2.9350
YEAR	1982	1994	2000	2000	2007	2014
COC_EMP_TALLY	0.000	0.000	1.000	3.127	4.000	32.000
COC_AP_TALLY	0.000	0.000	2.000	5.837	9.000	49.000
OP_EMP_TALLY	0.000	2.000	4.000	7.209	10.000	67.000
OP_AP_TALLY	0.000	0.000	0.000	2.153	2.000	60.000

XI. Additional Discussion

The results from this analysis's t-tests not only justify, but necessitate a reliable regression, one that I was unable to provide given my fixed position in time. The poverty of yearly drug use data has been discussed earlier in this paper, but it bears mentioning that the media response variable suffers the same shortcoming: the opioid epidemic is less than a decade old, and mentions of the specific phrase "opioid epidemic" don't occur with any frequency (at least not in the New York Times) until around 2011. By contrast, the crack epidemic has aged over 30 years — it's arguably mentioned more in newspapers retrospectively at this point than it was contemporaneously. This disparity forces the analysis I ran in an uncomfortable direction — rather than specifically target either epidemic in the regression as I did successfully in the t-tests, I had to use more frequently used, but more general words like heroin, which, between the 1980s and today, include many references to irrelevant information like the way in which heroin helped spread the AIDS epidemic or exposés about large-scale heroin dealing in other countries like China.

A search like this obscures reference to more relevant information, like discussion of heroin overdoses in America. It's these articles that reveal the most apparent racial bias, where heroin addicts are treated like victims of an unfortunate affliction rather than morally corrupt addicts, as many crack-addicted patients were in crack-related articles pulled for this analysis. This inability to pin down any specific long-term trend in word-search data (many analyses were tried, i.e. "crack cocaine," "crack epidemic," "cocaine," "heroin

epidemic,” “heroin crisis,” and “heroin overdose,” among others) represents this paper’s most significant weakness.

Secondly, it’s likely that a feedback effect exists within the media response variable between past and future newspaper articles. For example, if stories about crack addiction broke as a result of crack’s initial spread into an urban black community, the drug may have gained a reputation as a “black” drug. This reputation could have caused a certain measure of neglect as the drug spread into white communities, ultimately focusing media coverage on addiction in the black community. In this hypothetical, little relationship would exist between the actual racial demographic of drug use; instead, initial use would cause a ripple effect forward, affecting all future media response.

Third, no overlap exists between the two epidemics. Each is situated in a different political, social, and economic climate. The crack epidemic occurred just 20 years after the peak of the civil rights movement, whereas the opioid epidemic began by some counts as recently as 2011. As such, we should expect differences to exist between the two that may have little to do with our willingness to tolerate or justify certain behaviors in the white community that we won’t tolerate or justify in the black community. In other words, we can’t be certain about how reporters would react to a primarily-black drug epidemic today or to a white opioid epidemic in 1990, and so must not confuse a difference across time with evidence of ongoing bias today.

Lastly, no additional regressions were run after the first. This was by design. Several subsequent attempts at re-scraping or re-framing word-search data failed to reveal anything beyond random assortment — in other words, a

scatterplot of media response data points to which nothing but a horizontal trendline could be fit. For this reason, it made no sense to run a second or third regression because no discernible relationship would be determined from a random assortment of data, and if one was, a high likelihood would exist that it emerged by chance. As such, neither an effect nor a lack thereof provides useful information.

Future researchers should not let this deter them, though. Untangling race from media response may be easier if comparing across states and popular state newspapers, for which state demographic drug use data may be easier to come by. Approaching such an analysis from a geographically — rather than temporally — diverse angle could yield insights into the same potential race-based effect, with none of the accompanying observation shortage issues. Likewise, the passage of time will leave room for a broader, more reliable longitudinal analyses similar to the one conducted here.

Lastly, the development of machine learning technology like Google's TensorFlow provides an avenue for a much sharper, much less arbitrary analysis of language use in the media. TensorFlow functions like a black box. You feed it info — for example: pictures of hand written digits — and tell it which digit each picture represents. You train the program on hundreds or thousands (in reality for a study like digit recognition, preferably tens of thousands) of examples, and then you can feed it a novel image of a handwritten digit and it will be able to tell you with high accuracy which digit is written. This is the way familiar functions like Google's image search work.

For the purposes of this analysis, it would make sense to train a program to recognize apathetic from empathetic articles, thereby unburdening the study from the arbitrary and inconsistent use of a handful of buzzwords. This method would not only be able to analyze hundreds of thousands of more articles, but would be able to distinguish between irrelevant and relevant articles as well as between generally apathetic articles and empathetic articles that reflect on the failings of previous media response (and thus mention many of the apathetic words in the word search). Ultimately, such a program would be able to tell whether, for example, an article about a heroin overdose patient that neither mentions any criminal justice nor public health buzzwords, differs significantly from an article about a crack overdose patient. Almost any difference a human can recognize, the program would be able to recognize, only exponentially more efficiently. Future analyses with more time and more resources should look into training such a machine learning program.

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Appendix

The analysis run to gather data for the regressions and the t-tests involved a Python web-scraping program that searched the New York Times article archive and collected the body content from each article. The code for that search can be viewed on github at https://github.com/ChampeBarton/Thesis_Data. In short, it used the New York Times article search API in order to search pre-assigned terms, then parsed each article in the search results, storing every individual word into a temporary list. That program then cycled through the list, comparing each element (in this case, each word) to a pre-defined comparison list of empathetic and apathetic words. It kept a running count of each match's occurrence that reset with each new article.



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