The Political Effects of Opioid Addiction Frames
Supplementary Online Appendix

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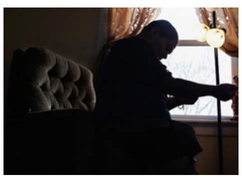
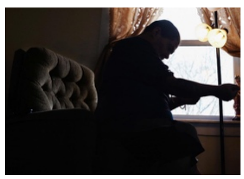
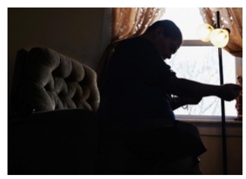
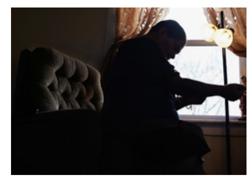
A.1 Experimental conditions: Contents

To heighten realism and create strong, distinct treatments, we incorporated multiple cues of valence and race. Bolded text indicates differences across treatments. Photos of "Mike" were generated by Tokeshi and Mendelberg (2015) using Facegen software.

Figure A1: Full text of news stories in experimental treatments

Treatment 1: Sympathetic White	Treatment 3: Sympathetic Black	Treatment 2: Unsympathetic White	Treatment 4: Unsympathetic Black
Instructions: Please review the following excerpt from a featured news story. After you finish reading, please answer the questions on the next page.	*Instructions: Please review the following excerpt from a featured news story. After you finish reading, please answer the questions on the next page.*	*Instructions: Please review the following excerpt from a featured news story. After you finish reading, please answer the questions on the next page.*	*Instructions: Please review the following excerpt from a featured news story. After you finish reading, please answer the questions on the next page.*
More Evidence Suggests That **Drug Companies** Helped Cause the Opioid Epidemic	More Evidence Suggests That **Drug Companies** Helped Cause the Opioid Epidemic	More Evidence Suggests That **Careless Patients** Helped Cause the Opioid Epidemic	More Evidence Suggests That **Careless Patients** Helped Cause the Opioid Epidemic
			
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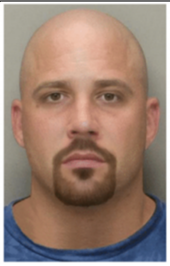
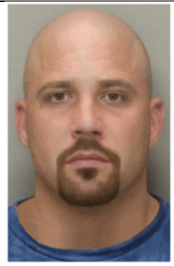
say these are 'deaths of **despair'.** Over the years, many medical professionals said that opioid addiction is **not** a serious danger. They **encouraged** patients prescribed opioids like OxyContin to use these for pain **from an ever-wider range of maladies.** **Sales representatives** disregarded warnings and **marketed** OxyContin and similar medications **as products "to start with and to stay with."** Many people **used** prescription opioids **as medically instructed**, but became severely addicted. Many addicts eventually found prescription painkillers too difficult to obtain and turned to heroin, a common narcotic. According to the American Society of Addiction Medicine, four out of five people who try heroin today started with **legal** prescription painkillers. Mike, a **White** American man living in Pennsylvania, is emblematic of the **people suffering from opioid addiction**.	say these are 'deaths of **despair'**. Over the years, many medical professionals said that opioid addiction is **not** a serious danger. They **encouraged** patients prescribed opioids like OxyContin to use these for pain **from an ever-wider range of maladies.** **Sales representatives** disregarded warnings and **marketed** OxyContin and similar medications **as products "to start with and to stay with."** Many people **used** prescription opioids **as medically instructed, but** became severely addicted. Many addicts eventually found prescription painkillers too difficult to obtain and turned to heroin, a common narcotic. According to the American Society of Addiction Medicine, four out of five people who try heroin today started with **legal** prescription painkillers. Mike, a **Black** American man living in Pennsylvania, is emblematic of the **people suffering from opioid addiction**.	say these are 'deaths of **irresponsibility'** . Over the years, many medical professionals said that opioid addiction is a serious danger. They **cautioned** patients prescribed opioids like OxyContin to use these **only** for pain. However, **some patients** disregarded warnings and **used** OxyContin and similar medications **recreationally.** Many people **abused** prescription opioids **against medical instructions**, **and** became severely addicted. Many addicts eventually found prescription painkillers too difficult to obtain and turned to heroin, a common narcotic. According to the American Society of Addiction Medicine, four out of five people who try heroin today started with **ill-obtained** prescription painkillers. Mike, a **White** American man living in Pennsylvania, is emblematic of the **addicts abusing opioids.**	say these are 'deaths of **irresponsibility'**. Over the years, many medical professionals said that opioid addiction is a serious danger. They **cautioned** patients prescribed opioids like OxyContin to use these **only** for pain. However, **some patients** disregarded warnings and used OxyContin and similar medications **recreationally**. Many people **abused** prescription opioids **against medical instructions**, **and** became severely addicted. Many addicts eventually found prescription painkillers too difficult to obtain and turned to heroin, a common narcotic. According to the American Society of Addiction Medicine, four out of five people who try heroin today started with **ill-obtained** prescription painkillers. Mike, a **Black** American man living in Pennsylvania, is emblematic of the **addicts abusing opioids.**

 When he was a teen-ager, he saw a doctor for a sports injury. The doctor prescribed an opioid, **never** warning him about its addictive potential. Mike **found it difficult** to stop. **The doctor kept refilling** the prescription. Mike had **never** been a drug user before then, even though he grew up in a neighborhood with drug dealers. In **unflinching** tones, Mike recounted the toll that opioids took over the next decade of his life: losing his girlfriend, who tried to help, but could **only do so much** and left Mike after becoming pregnant with his child; and difficulty finding employers willing to **give an addict a chance** at a job. He **never** became an absent father, **and always pays** child support to his ex-girlfriend. He **sees** his three-year-old son **every week.** He kept **trying** to kick the habit, but opioids **were 'everywhere'.** Eventually, friends told him he really had a	 When he was a teen-ager, he saw a doctor for a sports injury. The doctor prescribed an opioid, **never** warning him about its addictive potential. Mike **found it difficult** to stop. **The doctor kept refilling** the prescription. Mike had **never** been a drug user before then, even though he grew up in a neighborhood with drug dealers. In **unflinching** tones, Mike recounted the toll that opioids took over the next decade of his life: losing his girlfriend, who tried to help, but could **only do so much** and left Mike after becoming pregnant with his child; and difficulty finding employers willing to **give an addict a chance at** a job. He **never** became an absent father, **and always pays** child support to his ex-girlfriend. He **sees** his three-year-old son **every week.** He kept **trying** to kick the habit, but opioids **were 'everywhere'.** Eventually, friends told him he really had a	 When he was a teen-ager, he saw a doctor for a sports injury. The doctor prescribed an opioid, warning him about its addictive potential. Mike **liked it too much** to stop. **He kept switching doctors to refill** the prescription. Mike had been a drug user before then, though he grew up in a neighborhood **free of** drug dealers. In **aggrieved** tones, Mike **reluctantly** recounted the toll that opioids took over the next decade of his life: losing his girlfriend, who tried to help, but could **not take his abuse** and left Mike after becoming pregnant with his child; and difficulty finding employers willing to **put up with an addict who couldn't hold** a job. He became an absent father, **owing thousands in** child support to his ex-girlfriend. He **has only seen** his three-year-old son **twice.** He kept **being told** to kick the habit, but opioids **made him feel great.** Eventually, friends told him he really had a problem. **"I didn't**	 When he was a teen-ager, he saw a doctor for a sports injury. The doctor prescribed an opioid, warning him about its addictive potential. Mike **liked it too much** to stop. **He kept switching doctors to refill** the prescription. Mike had been a drug user before then, though he grew up in a neighborhood **free of** drug dealers. In **aggrieved** tones, Mike **reluctantly** recounted the toll that opioids took over the next decade of his life: losing his girlfriend, who tried to help, but could **not take his abuse** and left Mike after becoming pregnant with his child; and difficulty finding employers willing to **put up with an addict who couldn't hold** a job. He became an absent father, **owing thousands in** child support to his ex-girlfriend. He **has only seen** his three-year-old son **twice**. He kept **being told** to kick the habit, but opioids **made him feel great.** Eventually, friends told him he really had a problem. **"I didn't**

problem. "**I realized I** have to look at myself. I told them 'I have a problem.'" **But** one day, **in the throes of withdrawal from** OxyContin, a friend said, "I'll sell you a bag of heroin for twenty bucks." Mike **at first** said **no**. **But as** the withdrawal **grew unbearable,** he acquiesced. He **tried** quitting heroin, "but **even though you desperately want to stop,** you just **can't "** he said. He started injecting it. He was **careful and only** used in private. His neighbors **did not know** he was addicted. They **never had to find him** passed out or used needles in their flowerpots. When he was evicted, he **was ashamed.** He **couldn't stand the idea that** the neighbors **would** stop letting their kids play outside so they wouldn't see him using. Mike **checked into** a treatment program. During the course of a year, **he stayed clean, but he relapsed when the pain from his old injury flared up.** He **wants** to go into treatment again. The waitlist is very long, but **he is determined to resist** the high.	problem. **"I realized I** have to look at myself. I told them 'I have a problem.'" **But** one day, **in the throes of withdrawal from** OxyContin**,** a friend said, "I'll sell you a bag of heroin for twenty bucks." Mike **at first** said **no. But as** the withdrawal **grew unbearable**, he acquiesced. He **tried** quitting heroin, "but **even though you desperately want to stop,** you just **can't "** he said. He started injecting it. He was **careful and only** used in **private.** His neighbors **did not know** he was addicted. They **never had to find him** passed out or used needles in their flowerpots. When he was evicted, he **was ashamed.** **He couldn't stand the idea that** the neighbors **would** stop letting their kids play outside so they wouldn't see him using. Mike **checked into** a treatment program. During the course of a year, **he stayed clean, but he relapsed when the pain from his old injury flared up.** He **wants** to go into treatment again. The waitlist is very long, but **he is determined to resist** the high.	**want to** have to look at myself. I told them 'I **don't** have a problem.'" One day, **he ran out of** OxyContin**,** and a friend said, "I'll sell you a bag of heroin for twenty bucks." Mike said **yes. He was not going to put up with** withdrawal**, and** he acquiesced**, disregarding the dangerous consequences.** He **thought about** quitting heroin, "but you just **don't feel like stopping ,"** he said. He started injecting it. He was **careless and often** used in **public.** His neighbors **knew** he was addicted. They **found him** passed out **in plain view** and used needles in their flowerpots. When he was evicted, he **started defecating in the street.** The neighbors stopped letting their kids play outside so they wouldn't see him using. Mike **knew he should check into** a treatment program. During the course of a year, **he made several appointments, but he didn't feel ready to make a change.** He **thinks about** going into treatment. The waitlist is **not** very long, but **he loves** the high.	**want to** have to look at myself. I told them 'I **don't** have a problem.'" One day, **he ran out of** OxyContin, and a friend said, "I'll sell you a bag of heroin for twenty bucks." Mike said **yes**. **He was not going to put up with** withdrawal, **and** he acquiesced, **disregarding the dangerous consequences.** He **thought about** quitting heroin, "but you just **don't feel like stopping,"** he said. He started injecting it. He was **careless and often** used in **public**. His neighbors **knew** he was addicted. They **found him** passed out **in plain view** and used needles in their flowerpots. When he was evicted, he **started defecating in the street.** The neighbors stopped letting their kids play outside so they wouldn't see him using. Mike **knew he should check into** a treatment program. During the course of a year, **he made several appointments, but he didn't feel ready to make a change.** He **thinks about** going into treatment. The waitlist is **not** very long, but **he loves** the high.

When we spoke with his mother on the steps of her neatly kept bungalow in Northwest Pennsylvania, she said: “**Mike** tried every approach in the book, including a treatment program. Change only comes when they **get access to treatment.** The people around opioid users also **benefit** when they **are offered** help. This allows the inherent **goodness beneath** the addiction to take over. Mike **never hurt** his little brother and **made sure he didn’t see** him overdose. He **never** stole money from me and **helped as much as he could when** I struggled to put food on the table for my children. He **never let** the consequences of his addiction touch our lives. That is **selfless**.” The story of Mike is being repeated in **rural towns** all over Pennsylvania, and many other states. These communities are struggling under the weight of problems their residents **did not create.** And there is no end in sight as the epidemic continues.	When we spoke with his mother on the steps of her neatly kept bungalow in Northwest Pennsylvania, she said: “**Mike** tried every approach in the book, including a treatment program. Change only comes when they **get access to treatment.** The people around opioid users also **benefit** when they **are offered** help. This allows the inherent **goodness beneath** the addiction to take over. Mike **never hurt** his little brother and **made sure he didn’t see** him overdose. He **never** stole money from me and **helped as much as he could when** I struggled to put food on the table for my children. He **never let** the consequences of his addiction touch our lives. That is **selfless**.” The story of Mike is being repeated in **inner cities** all over Pennsylvania, and many other states. These communities are struggling under the weight of problems their residents **did not create**. And there is no end in sight as the epidemic continues.	When we spoke with his mother on the steps of her neatly kept small bungalow in Northwest Pennsylvania, she said: “**I** tried every approach in the book, including **asking Mike to try** a treatment program. Change only comes when they **really want to change.** The people around opioid abusers also **hurt** when they **repeatedly reject** help and allow the inherent **selfishness of** the addiction to take over. Mike **traumatized** his little brother **who saw** him overdose **and thought he was watching him die.** He stole money from me and I struggled to put food on the table for my children. He **forced** the consequences of his addiction into our lives. That is **cruel**.” The story of Mike is being repeated in **rural towns** all over Pennsylvania, and many other states. These communities are struggling under the weight of problems their **least responsible** residents **have created**. And there is no end in sight as the epidemic continues.	When we spoke with his mother on the steps of her neatly kept small bungalow in Northwest Pennsylvania, she said: “**I** tried every approach in the book, including **asking Mike to try** a treatment program. Change only comes when they **really want to change.** The people around opioid abusers also **hurt** when they **repeatedly reject** help and allow the inherent **selfishness of** the addiction to take over. Mike **traumatized** his little brother **who saw** him overdose and **thought he was watching him die**. He stole money from me and I struggled to put food on the table for my children. He **forced** the consequences of his addiction into our lives. That is **cruel**.” The story of Mike is being repeated in **inner cities** all over Pennsylvania, and many other states. These communities are struggling under the weight of problems their **least responsible** residents **have created.** And there is no end in sight as the epidemic continues.

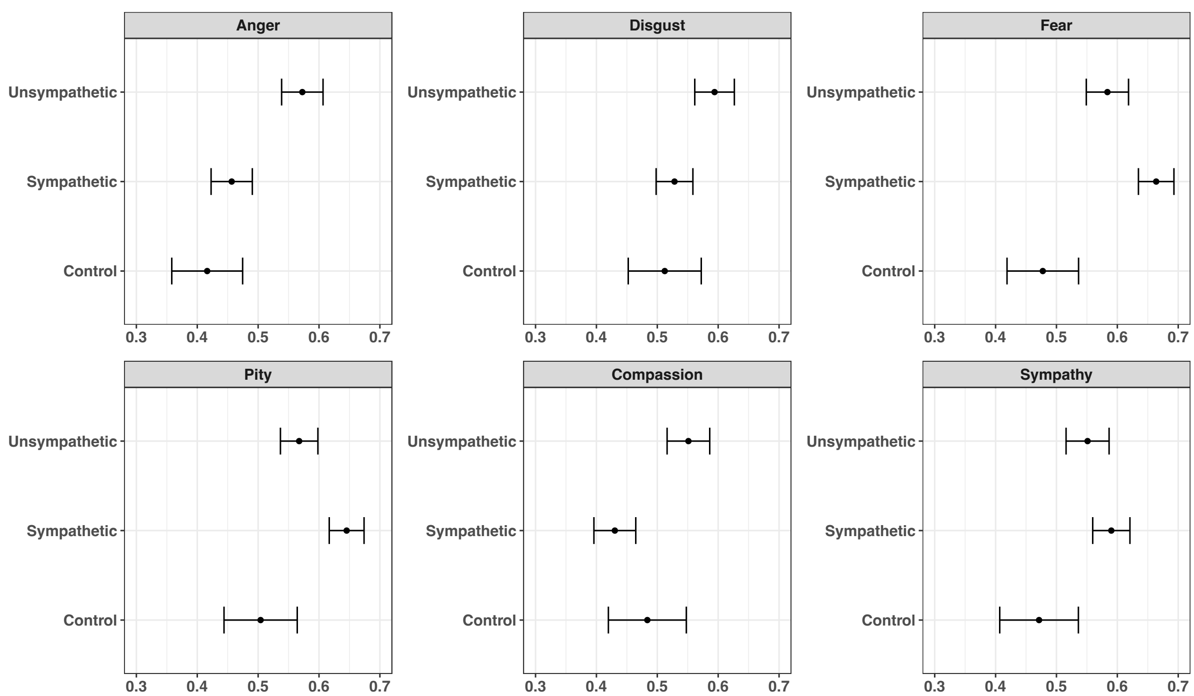
A.2 Equations (abbreviations are defined in Table 1 in the main paper)

- Equation 1: $DV = a + b1_1SW + b2_1SB$ [C baseline]
  - Tests: Sympathy and Anti-Black hypotheses
- Equation 2: $DV = a + b1_2SB$ [SW baseline]
  - Tests: Racially selective sympathy hypothesis
- Equation 3: $DV = a+ b1_3UW +b2_3UB$ [C baseline]
  - Tests: Antipathy and Pro-White bias hypotheses
- Equation 4: $DV = a+ b1_4UB$ [UW baseline]
  - Tests: Racial antipathy hypothesis
- Equation 5: $DV = a+ b1_5SW$ [UW baseline]
  - Tests: Full valence hypothesis
- Equation 6: $DV = a + b1_6SB$ [UB baseline]
  - Tests: Full valence hypothesis
- Equation 7: $DV = a + b1_7(SB + UB)$ [(SW + UW) baseline]
  - Tests: Racial main effect hypothesis

A.3 Dynata study[1] outcomes

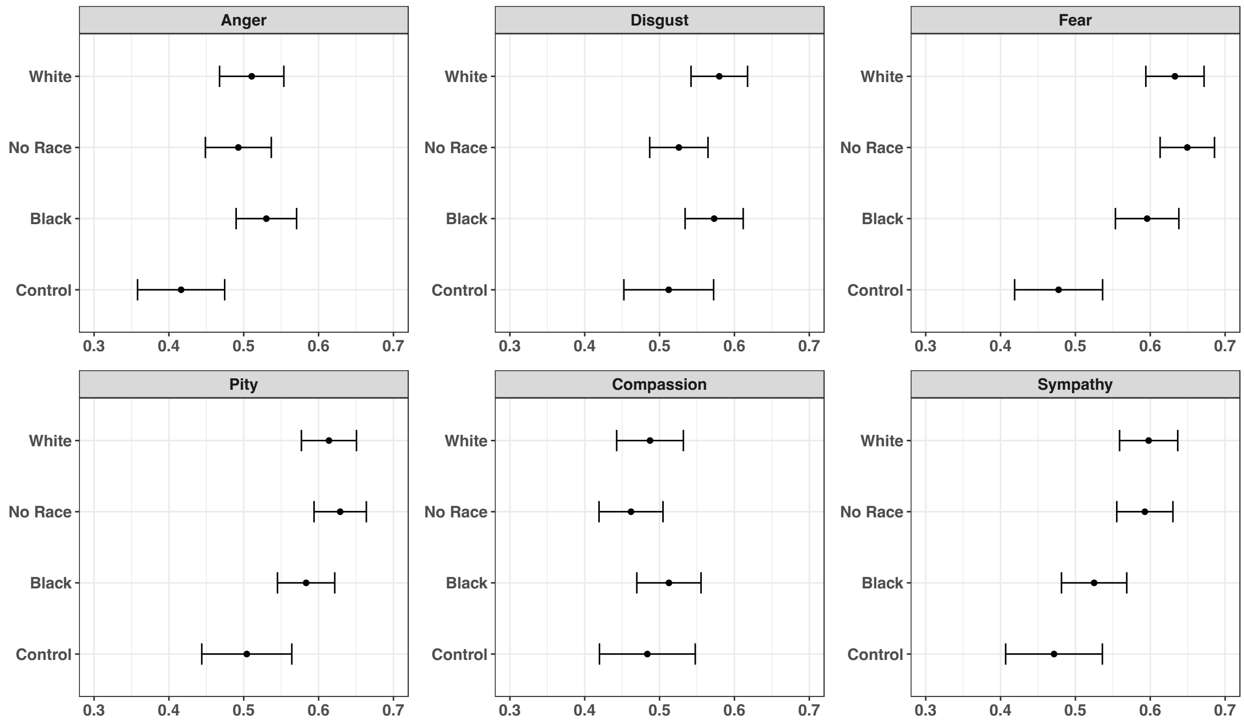
The emotions in the Dynata study are not sufficiently correlated to scale together.

Figure A2: Mean emotional responses to 'drug addicts', by valence condition (raw values, 83% CIs)



[1] A preliminary pre-test was conducted on 325 White American MTurk respondents prior to the Dynata study. The frames were revised to strengthen sympathetic and unsympathetic valence before the Dynata pre-test. Results available upon request.

Figure A3: Mean emotional responses to 'drug addicts', by racial condition (raw values, 83% CIs)

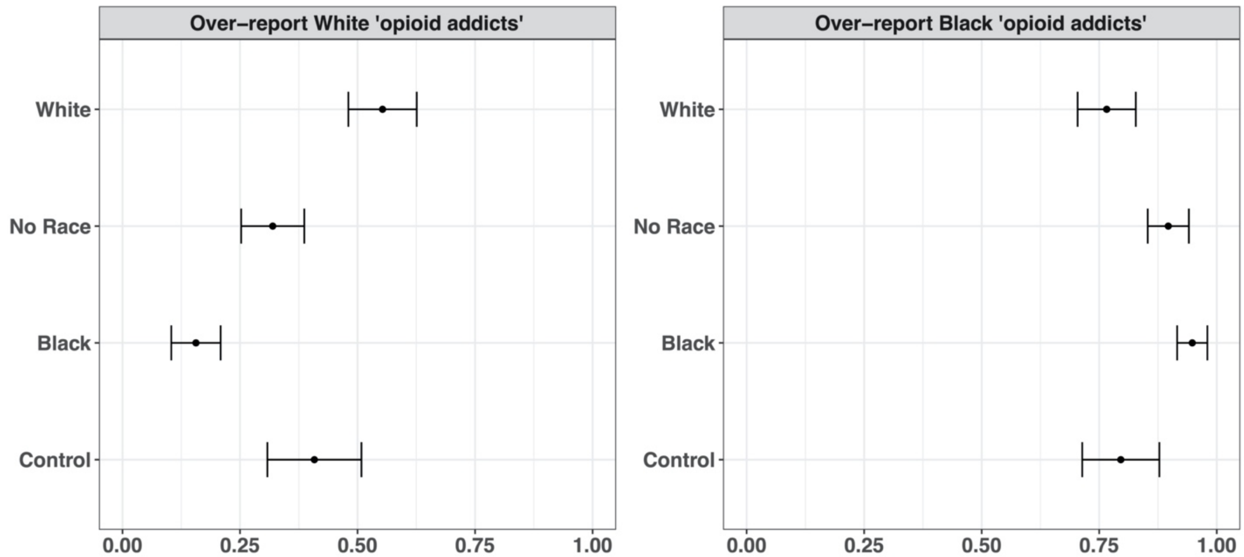


Appendix Figure A3 shows emotions are statistically indistinguishable by racial frame. Compared to the control, the pooled Black conditions significantly increase anger and fear, while the pooled White conditions significantly increase pity, sympathy, and fear. The Black and White conditions do not differ significantly from each other on anger, disgust, fear, pity or compassion, and differ on sympathy at a marginally significant p = 0.08.

The no-race conditions resemble the White conditions on pity and sympathy. This suggests cumulative exposure to the White face of the epidemic has created an association between opioid abuse, Whites, and sympathy that does not require direct references to Whites to be activated.

White identity and racial stereotypes do not moderate the racial effects on emotional outcomes. We do not present the moderating effects of racial resentment because it is affected by the sympathetic White treatment.

Figure A4: Prop. over-reporting White and Black 'opioid addicts,' by racial condition (raw values, 83% CIs)



A.4 Additional manipulation checks

A.4.1 Dynata study

To validate the racial conditions, we asked "What was the race of Mike, the person discussed in the article?". Mike's race was perceived correctly by nearly every respondent in both the White and Black conditions. Specifically, "Mike" was perceived as White by 97% of those in the White conditions and 6% of those in the Black conditions. "Mike" was perceived as Black by 93% of those in the Black conditions and 1% in the White conditions. Response options are "White or Caucasian," "Black or African American," "No race," and "Not sure."

A.4.2 Main study

To validate the valence conditions, we asked "How much sympathy do you feel towards Mike?". Responses range from "I do not feel any sympathy" (0) to "A great deal of sympathy" (1). To validate the racial conditions, we used the same over-reporting variables described in the paper. Consistent with the Dynata results, the sympathetic treatments significantly increased sympathy relative the unsympathetic treatments (Table A1), and the racial frames significantly affected racial perceptions of opioid addicts (Table A2).

Table A1: Valence manipulation check (Baseline = Pooled Unsympathetic)

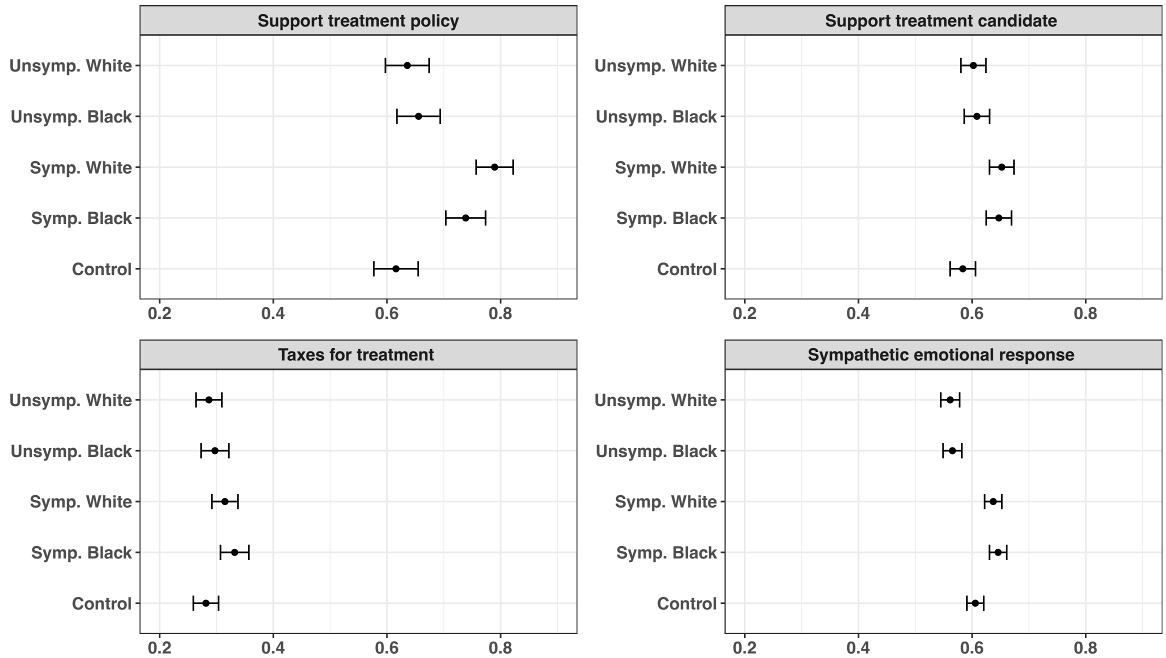
	Sympathy for Mike (OLS)	
	(1)	(2)
Pooled Sympathetic	0.186	0.194
	(.016)	(.016)
Const.	0.452	0.605
	(.012)	(.054)
Controls	N	Y
Obs.	1,213	1,079
Adj. R^2	0.097	0.170

Table A2: Racial perception manipulation check (Baseline = C)

	Over-report White addicts (yes/no) (Logit)		Over-report Black addicts (yes/no) (Logit)	
	(1)	(2)	(3)	(4)
Pooled White	0.571	0.576	-0.556	-0.575
	(.149)	(.164)	(.197)	(.212)
Pooled Black	-0.935	-0.968	1.235	1.266
	(.169)	(.181)	(.263)	(.275)
Const.	-0.800	-0.072	1.872	0.704
	(.125)	(.429)	(.170)	(.566)
Controls	N	Y	N	Y
Obs.	1,512	1,353	1,512	1,353

A.5 Raw means by experimental condition, main study

Figure A5: Mean outcome values across experimental conditions (raw values, 83% CIs)



A.6 Variable information and regression tables, main study

"Treatment policy" is a binary variable modeled with logistic regression. The remaining outcomes are modeled with OLS. All outcome variables, pre-treatment covariates, and racial predisposition moderators are defined in Table A3 below.

Table A3: Outcome variables, pre-treatment covariates, and racial predisposition moderators

Variable	Question	Coding
	Outcome variables	
Treatment policy	"Do you think drug addicts should be arrested for violating drug laws, or offered government-funded treatment?"	A binary variable, 0 = Favoring arrest, 1 = Favoring treatment
Treatment candidate	"How likely would you be to vote for a political candidate who advocates for government-funded drug treatment programs over arresting drug addicts for violating the law?"	A five-point variable ranging from "Extremely unlikely" (0) to "Extremely likely" (1)
Taxes for treatment	"Regardless of how you answered the prior question, how much money in extra taxes would you personally be willing to pay for government-funded treatment programs?"	A six-point variable ranging from "$0" (0) to "$300 or more" (1)

Emotions towards drug addicts	"Which of the following emotions, if any, do you feel towards drug addicts?" [Anger, fear, disgust, sympathy][2]	Eleven-point scales ranging from "I don't feel this emotion" (0) to "I feel this emotion strongly" (1). Anger, fear, and disgust are reverse coded and averaged with sympathy into a four-item index ranging from most negative (0) to most positive (1), alpha = 0.67
Pre-treatment covariates		
Age	What is your date of birth?	Coded as numeric age in 2020
Region	In which state do you currently reside?	Coded as a set of dummy variables: "South" (baseline), "Northeast," "Midwest," "West"
Level of education	What is the highest level of school you have completed?	Coded as a set of dummy variables: "Less than high school" (baseline), "High school graduate," "Some college," "College graduate," "Post-graduate"
Income	Which of the following includes your total household income in 2019 before taxes?	Coded as a set of dummy variables: "Less than $25,000" (baseline), "$25,000 to $34,000," "$35,000 to $49,0000," "$50,000 to $74,999," "$75,000 to $99,999," "$100,000 to $149,999," "$150,000 or more"
Gender	"Are you:"	A binary variable, 0 = Male, 1 = Female
Partisanship[3]	"Generally speaking, do you usually think of yourself as a Republican, a Democrat, an Independent or what?" "Would you call yourself a Strong Republican/Democrat or a moderate Republican/Democrat?" "Do you lean more towards the Democrats or Republicans"	A seven-point measure, ranging from "Strong Democrat"(1) to "Strong Republican" (7). Rescaled on the 0 to 1 interval for use as covariate in regressions
Ideology	"When it comes to politics, do you usually think of yourself as...?"	A seven-point measure, ranging from "Extremely Liberal" (1) to "Extremely Conservative" (7)

[2] These emotions, along with compassion and pity, are also included in the Dynata study.
[3] Partisanship and ideology are also used in the moderator analyses. Variable coding for this analysis is described below.

Racial predisposition moderators		
Racial resentment	Two-item index: (1) "The Irish, Italians, Jews, and many other minorities overcame prejudice and worked their way up. Blacks should do the same without any special favors. (2) "Generations of slavery and discrimination have created conditions that make it difficult for Blacks to work their way out of the lower class.	A five-point variable ranging from "Agree strongly" to "Disagree strongly." Items are scaled on the 0 to 1 interval, where 1 is more racially resentful
White identity	"As you know, people have different identities. They think of themselves as black, white, etc. We would like to ask you how you think about yourself. How important is being White to your identity?"	A five-point variable ranging from "Not at all important" to "Extremely important." Items are scaled on the 0 to 1 interval, where 1 is more racially identified
Racial stereotypes	Two-item index: "In the next statement, a score of '1' means that you think almost all of the people in that group tend to be 'hard-working,' a score of '7' means that you think most people in that group are 'lazy.' A score of '4' means that you think most people in the group are not closer to one end or the other, and of course, you may choose any number in between. Where would you rate the following groups in general on this scale: Blacks; Whites."	A seven-point measure, rescaled on the 0 to 1 interval, subtracting stereotypes of Whites from those of Blacks, where 1 is more racially biased.

A.6.1 Main effects

Tables A4-A10 report results for Figures 1-3. Even-numbered columns include pre-treatment controls: age, region, education, gender, income, partisanship, and ideology. Odd-numbered columns omit controls.

Table A4: Sympathy & anti-Black hypotheses (Equation 1, Baseline = Control)

	Treatment policy		Candidate		Taxes		Emotions	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sympathetic White	0.850 (.184)	1.228 (.229)	0.069 (.022)	0.079 (.021)	0.033 (.024)	0.037 (.024)	0.032 (.015)	0.044 (.016)
Sympathetic Black	0.566 (.176)	0.673 (.211)	0.063 (.022)	0.058 (.021)	0.051 (.024)	0.050 (.023)	0.040 (.015)	0.049 (.015)
Const.	0.472 (.118)	2.916 (.598)	0.584 (.016)	0.869 (.054)	0.281 (.017)	0.414 (.061)	0.606 (.011)	0.700 (.040)
Obs.	912	812	912	812	911	812	909	809
Adj. R^2	--	--	0.010	0.262	0.003	0.152	0.006	0.085

Table A5: Racially selective sympathy hypothesis (Equation 2, Baseline = Sympathetic White)

	Treatment policy		Candidate		Taxes		Emotions	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sympathetic Black	-0.283	-0.565	-0.005	-0.021	0.017	0.014	0.009	0.004
	(.192)	(.231)	(.022)	(.021)	(.024)	(.024)	(.015)	(.016)
Const.	1.322	3.875	0.652	0.941	0.315	0.487	0.637	0.762
	(.141)	(.859)	(.016)	(.070)	(.017)	(.080)	(.011)	(.053)
Obs.	610	537	610	537	609	537	608	535
Adj. R^2	--	--	-0.002	0.226	-0.001	0.157	-0.001	0.055

Table A6: Antipathy & pro-White hypothesis (Equation 3, Baseline = Control)

	Treatment policy		Candidate		Taxes		Emotions	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unsympathetic White	0.085	0.149	0.019	0.012	0.005	0.003	-0.044	-0.041
	(.168)	(.200)	(.023)	(.021)	(.024)	(.023)	(.016)	(.017)
Unsympathetic Black	0.172	0.070	0.025	0.022	0.016	0.015	-0.040	-0.038
	(.169)	(.199)	(.023)	(.021)	(.024)	(.023)	(.016)	(.017)
Const.	0.472	2.206	0.584	0.943	0.281	0.383	0.606	0.683
	(.118)	(.520)	(.016)	(.054)	(.017)	(.061)	(.012)	(.043)
Obs.	906	818	907	819	906	818	905	817
Adj. R^2	--	--	-0.001	0.259	-0.002	0.125	0.008	0.079

Table A7: Racial antipathy hypothesis (Equation 4, Baseline = Unsympathetic White)

	Treatment policy		Candidate		Taxes		Emotions	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unsympathetic Black	0.087	-0.064	0.006	0.011	0.011	0.012	0.004	0.004
	(.170)	(.198)	(.023)	(.021)	(.024)	(.024)	(.017)	(.018)
Const.	0.557	1.814	0.602	0.980	0.287	0.403	0.561	0.633
	(.120)	(.651)	(.016)	(.070)	(.017)	(.080)	(.012)	(.057)
Obs.	604	543	605	544	604	543	604	543
Adj. R^2	--	--	-0.002	0.225	-0.001	0.114	-0.002	0.063

Table A8: Full valence hypothesis (Equation 5, Baseline = Unsympathetic White)

	Treatment policy		Candidate		Taxes		Emotions	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sympathetic White	0.765	1.015	0.050	0.071	0.028	0.030	0.076	0.082
	(.185)	(.225)	(.022)	(.021)	(.023)	(.024)	(.016)	(.017)
Const.	0.557	2.920	0.602	1.040	0.287	0.418	0.561	0.624
	(.120)	(.831)	(.016)	(.070)	(.016)	(.080)	(.011)	(.057)
Obs.	606	533	607	534	605	533	606	533
Adj. R^2	--	--	0.007	0.250	0.001	0.117	0.033	0.099

Table A9: Full valence hypothesis (Equation 6, Baseline = Unsympathetic Black)

	Treatment policy		Candidate		Taxes		Emotions	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sympathetic Black	0.395	0.498	0.039	0.037	0.035	0.038	0.080	0.083

	(.178)	(.204)	(.023)	(.022)	(.025)	(.025)	(.016)	(.017)
Const.	0.644	1.691	0.608	0.850	0.297	0.462	0.565	0.675
	(.121)	(.639)	(.016)	(.068)	(.018)	(.078)	(.011)	(.053)
Obs.	608	547	608	547	608	547	606	545
Adj, R^2	--	--	0.003	0.226	0.001	0.159	0.038	0.091

Table A10: Racial main effect hypothesis (Equation 7, Baseline = Pooled White)

	Treatment policy		Candidate		Taxes		Emotions	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pooled Black	-0.075	-0.257	0.001	-0.007	0.014	0.011	0.006	0.004
	(.126)	(.146)	(.016)	(.015)	(.017)	(.017)	(.012)	(.012)
Const.	0.909	2.464	0.627	0.960	0.301	0.443	0.599	0.694
	(.090)	(.493)	(.011)	(.049)	(.012)	(.056)	(.008)	(.040)
Obs.	1,214	1,080	1,215	1,081	1,213	1,080	1,212	1,078
Adj. R^2	--	--	-0.001	0.226	-0.0003	0.140	-0.001	0.049

A.6.2 Moderator effects

Racial Predispositions (RP): Racial Resentment (RR), Racial Stereotypes (RS), and White Identity (WI)

Tables A11-A15 present racial predisposition interaction results. Each column includes a different racial moderator. Entries are logit coefficients for treatment policy and OLS for the rest, with standard errors in parentheses. Moderator analyses test all but the full valence hypothesis, as it is not relevant. All models include the standard pre-treatment covariates.

Racial resentment and White identity are divided into terciles and included as indicator variables, with the low tercile as the omitted baseline. We do so because binning continuous variables is best practice for interaction models (Hainmueller, Mummolo, and Xu 2019). As another advantage, terciles make these variables categorical and thus equivalent in measurement to ideology and partisanship. Racial stereotypes uses a binary split because it lacks sufficient variation for terciles.

The results show significant interaction effects for racial stereotypes and racial resentment for several outcomes but no statistically significant interactions for White identity.[4]

Table A11: Sympathy & anti-Black hypotheses (Equation 1, Baseline = Control), Racial Predisposition (RP) Moderators

	Treatment policy			Candidate			Taxes			Emotions		
	RR	RS	WID	RR	RS	WID	RR	RS	WID	RR	RS	WID
SW	1.347	1.089	1.241	0.073	0.080	0.118	0.023	0.037	0.060	0.033	0.039	0.054
	(.611)	(.262)	(.349)	(.034)	(.023)	(.033)	(.039)	(.027)	(.038)	(.026)	(.017)	(.025)
SB	1.569	0.774	0.952	0.092	0.057	0.074	0.091	0.046	0.045	0.045	0.050	0.066
	(.672)	(.241)	(.333)	(.033)	(.023)	(.033)	(.038)	(.026)	(.037)	(.026)	(.017)	(.025)
High RP	-1.655 (.427)	-0.203 (.358)	0.270 (.327)	-0.19 (.039)	-0.046 (.038)	0.051 (.033)	-0.202 (.044)	-0.041 (.043)	0.053 (.037)	-0.118 (.030)	-0.101 (.028)	-0.037 (.025)

[4] Four of twenty interaction models between racial resentment and treatment indicators and three of twenty corresponding models for racial stereotypes produce statistically significant effects.

Mid RP	-0.760 (.404)	--	0.371 (.387)	-0.078 (.036)	--	0.031 (.039)	-0.12 (.041)	--	0.032 (.044)	-0.073 (.028)	--	-0.029 (.029)
SW X High RP	0.258 (.695)	0.489 (.516)	0.032 (.495)	0.058 (.048)	-0.004 (.051)	-0.048 (.047)	0.019 (.055)	-0.001 (.059)	-0.051 (.053)	0.048 (.037)	0.027 (.038)	-0.014 (.035)
SB X High RP	-0.908 (.748)	-0.550 (.516)	-0.490 (.481)	-0.065 (.048)	0.0003 (.054)	-0.026 (.047)	-0.093 (.055)	0.011 (.061)	0.023 (.053)	0.005 (.037)	-0.025 (.039)	-0.038 (.035)
SW X Mid RP	-0.553 (.718)	--	-0.037 (.643)	-0.043 (.050)	--	-0.096 (.057)	0.027 (.057)	--	0.005 (.065)	-0.017 (.038)	--	-0.047 (.042)
SB X Mid RP	-0.908 (.762)	--	-0.524 (.570)	-0.029 (.049)	--	-0.018 (.055)	-0.021 (.056)	--	-0.019 (.063)	0.015 (.038)	--	-0.027 (.041)
Const.	2.476 (.650)	2.327 (.595)	2.151 (.624)	0.828 (.055)	0.825 (.054)	0.805 (.058)	0.389 (.062)	0.380 (.062)	0.357 (.065)	0.726 (.042)	0.708 (.040)	0.723 (.043)
Obs.	811	811	806	811	811	806	811	811	806	808	808	803
Adj. R^2	--	--	--	0.317	0.264	0.263	0.210	0.152	0.151	0.113	0.124	0.099

Table A12: Racially selective sympathy hypothesis (Equation 2, Baseline = Sympathetic White), Racial Predisposition (RP) Moderators

	Treatment policy			Candidate			Taxes			Emotions		
	RR	RS	WID	RR	RS	WID	RR	RS	WID	RR	RS	WID
SB	0.144 (.796)	-0.319 (.267)	-0.387 (.342)	0.018 (.035)	-0.024 (.024)	-0.053 (.033)	0.068 (.041)	0.011 (.027)	-0.018 (.038)	0.011 (.027)	0.009 (.018)	0.008 (.024)
High RP	-1.684 (.607)	0.196 (.392)	0.094 (.384)	-0.172 (.040)	-0.060 (.037)	-0.008 (.035)	-0.179 (.047)	-0.038 (.043)	-0.009 (.040)	-0.077 (.031)	-0.079 (.028)	-0.052 (.026)
Mid RP	-1.545 (.612)	--	0.293 (.516)	-0.143 (.038)	--	-0.070 (.043)	-0.101 (.045)	--	0.029 (.049)	-0.095 (.030)	--	-0.075 (.032)
SB X High RP	-1.123 (.857)	-1.115 (.540)	-0.337 (.523)	-0.121 (.048)	0.002 (.053)	0.040 (.049)	-0.113 (.056)	0.006 (.062)	0.082 (.056)	-0.044 (.038)	-0.049 (.040)	-0.019 (.037)
SB X Mid RP	-0.221 (.893)	--	-0.428 (.665)	0.018 (.051)	--	0.086 (.058)	-0.042 (.060)	--	-0.019 (.067)	0.034 (.040)	--	0.023 (.044)
Const.	3.778 (.999)	3.223 (.859)	3.311 (.877)	0.915 (.068)	0.910 (.071)	0.937 (.073)	0.449 (.080)	0.455 (.082)	0.463 (.083)	0.775 (.054)	0.758 (.053)	0.783 (.054)
Obs.	536	537	531	536	537	531	536	537	531	534	535	529
Adj. R^2	--	--	--	0.307	0.230	0.228	0.220	0.156	0.155	0.086	0.097	0.074

Table A13: Antipathy & pro-White hypothesis (Equation 3, Baseline = Control), Racial Predisposition (RP) Moderators

	Treatment policy			Candidate			Taxes			Emotions		
	RR	RS	WID	RR	RS	WID	RR	RS	WID	RR	RS	WID

UW	0.436 (.471)	-0.005 (.225)	0.196 (.326)	0.044 (.034)	-0.002 (.023)	0.016 (.034)	0.014 (.039)	-0.003 (.026)	0.013 (.039)	-0.048 (.027)	-0.051 (.018)	-0.045 (.027)
UB	0.621 (.506)	0.111 (.223)	-0.094 (.312)	0.055 (.034)	0.010 (.023)	0.031 (.033)	0.037 (.039)	-0.003 (.026)	0.035 (.037)	-0.010 (.028)	-0.046 (.018)	-0.065 (.026)
High RP	-1.759 (.415)	-0.207 (.349)	0.291 (.319)	-0.185 (.039)	-0.035 (.038)	0.055 (.033)	-0.221 (.044)	-0.045 (.043)	0.056 (.037)	-0.139 (.031)	-0.092 (.030)	-0.043 (.027)
Mid RP	-0.812 (.398)	--	0.309 (.383)	-0.068 (.036)	--	0.028 (.039)	-0.134 (.041)	--	0.028 (.044)	-0.073 (.029)	--	-0.041 (.031)
UW X High RP	-0.095 (.565)	0.688 (.496)	-0.209 (.445)	-0.014 (.048)	0.070 (.053)	-0.018 (.047)	-0.009 (.054)	0.023 (.060)	-0.044 (.053)	0.014 (.039)	0.044 (.042)	-0.014 (.037)
UB X High RP	-0.410 (.601)	-0.425 (.517)	0.261 (.446)	-0.024 (.049)	0.054 (.056)	-0.017 (.047)	-0.041 (.055)	0.088 (.063)	-0.074 (.053)	-0.043 (.039)	0.016 (.044)	0.033 (.037)
UW X Mid RP	-0.488 (.586)	--	0.331 (.603)	-0.071 (.050)	--	0.012 (.059)	-0.002 (.057)	--	0.042 (.066)	0.023 (.041)	--	0.054 (.047)
UB X Mid RP	-0.775 (.602)	--	0.536 (.565)	-0.064 (.049)	--	0.005 (.056)	-0.008 (.055)	--	0.054 (.064)	-0.029 (.040)	--	0.056 (.045)
Const.	1.889 (.585)	2.072 (.526)	1.737 (.554)	0.844 (.055)	0.879 (.054)	0.844 (.057)	0.328 (.062)	0.345 (.061)	0.307 (.064)	0.701 (.044)	0.720 (.043)	0.727 (.046)
Obs.	817	816	817	818	817	818	817	816	817	816	815	816
Adj. R^2	--	--	--	0.308	0.261	0.258	0.189	0.125	0.130	0.132	0.094	0.084

Table A14: Racial antipathy hypothesis (Equation 4, Baseline = Unsympathetic White), Racial Predisposition (RP) Moderators

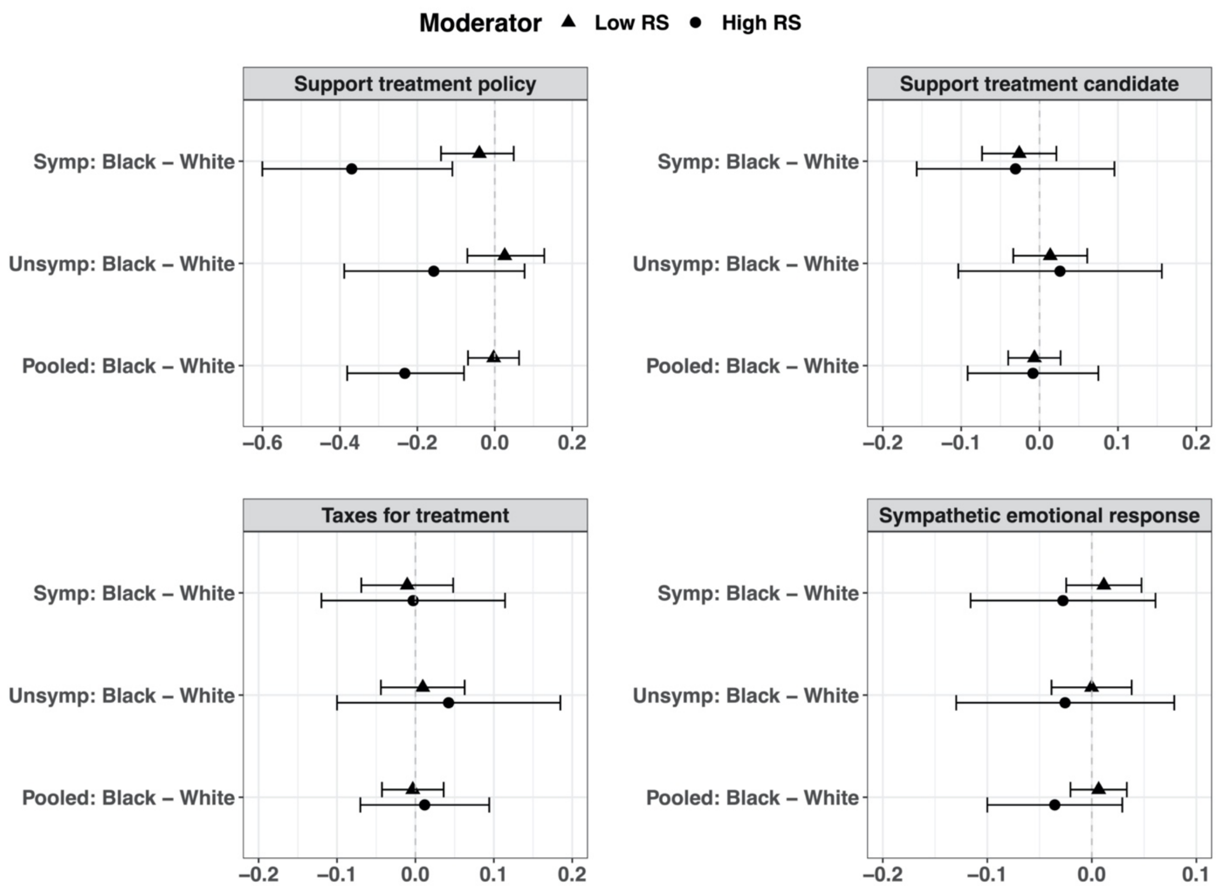
	Treatment policy			Candidate			Taxes			Emotions		
	RR	RS	WID	RR	RS	WID	RR	RS	WID	RR	RS	WID
UB	0.133 (.539)	0.117 (.220)	-0.268 (.306)	0.012 (.035)	0.013 (.023)	0.016 (.034)	0.025 (.041)	0.002 (.027)	0.023 (.039)	0.037 (.029)	0.006 (.019)	-0.019 (.028)
High RP	-2.164 (.457)	0.365 (.365)	0.078 (.311)	-0.225 (.039)	0.028 (.041)	0.037 (.034)	-0.233 (.045)	-0.018 (.046)	0.011 (.039)	-0.140 (.032)	-0.053 (.033)	-0.057 (.028)
Mid RP	-1.509 (.460)	--	0.658 (.458)	-0.156 (.039)	--	0.043 (.045)	-0.138 (.045)	--	0.069 (.051)	-0.061 (.033)	--	0.015 (.037)
U.B. X High RP	-0.282 (.619)	-1.080 (.526)	0.476 (.437)	-0.013 (.049)	-0.016 (.058)	-0.001 (.048)	-0.037 (.056)	0.057 (.067)	-0.030 (.054)	-0.056 (.041)	-0.025 (.048)	0.049 (.039)
U.B. X Mid RP	-0.177 (.639)	--	0.148 (.606)	0.008 (.052)	--	-0.008 (.060)	-0.005 (.059)	--	0.014 (.068)	-0.050 (.043)	--	0.003 (.049)
Const.	1.958 (.733)	1.851 (.667)	1.647 (.680)	0.900 (.068)	0.909 (.070)	0.885 (.073)	0.344 (.079)	0.365 (.081)	0.336 (.083)	0.632 (.057)	0.662 (.058)	0.664 (.060)
Obs.	542	542	542	543	543	543	542	542	542	542	542	542
Adj. R^2	--	--	--	0.297	0.227	0.223	0.186	0.113	0.121	0.130	0.072	0.068

Table A15: Racial main effect hypothesis (Equation 7, Baseline = Pooled White), Racial Predisposition (RP) Moderators

	Treatment policy			Candidate			Taxes			Emotions		
	RR	RS	WID	RR	RS	WID	RR	RS	WID	RR	RS	WID
Pooled Black	0.206	-0.041	-0.267	0.015	-0.007	-0.024	0.046	0.004	-0.002	0.027	0.009	-0.011

	(.441)	(.165)	(.220)	(.025)	(.017)	(.023)	(.029)	(.019)	(.027)	(.021)	(.013)	(.019)
High RP	-1.896	0.320	0.059	-0.199	-0.012	0.010	-0.207	-0.030	-0.002	-0.112	-0.060	-0.066
	(.354)	(.256)	(.232)	(.028)	(.027)	(.024)	(.032)	(.031)	(.027)	(.023)	(.022)	(.019)
Mid RP	-1.430	--	0.473	-0.149	--	-0.017	-0.119	--	0.051	-0.079	--	-0.038
	(.358)		(.332)	(.027)		(.031)	(.032)		(.035)	(.023)		(.025)
Pooled Black X High RP	-0.700	-1.092	0.069	-0.071	-0.009	0.023	-0.077	0.031	0.029	-0.053	-0.046	0.023
	(.489)	(.362)	(.321)	(.034)	(.039)	(.034)	(.039)	(.045)	(.038)	(.028)	(.031)	(.027)
Pooled Black X Mid RP	-0.314	--	-0.141	0.008	--	0.045	-0.026	--	-0.004	-0.012	--	0.022
	(.508)		(.435)	(.036)		(.042)	(.042)		(.048)	(.030)		(.034)
Const.	2.626	2.345	2.256	0.913	0.918	0.921	0.399	0.415	0.395	0.709	0.715	0.732
	(.567)	(.503)	(.511)	(.048)	(.050)	(.051)	(.055)	(.057)	(.058)	(.040)	(.040)	(.041)
Obs.	1,078	1,079	1,073	1,079	1,080	1,074	1,078	1,079	1,073	1,076	1,077	1,071
Adj. R^2	--	--	--	0.302	0.227	0.226	0.209	0.140	0.141	0.097	0.071	0.061

Figure A6: Comparing Black and White treatments (Racial hypotheses, by racial stereotypes)



Estimates are percentage point marginal effects from separate Logit (for policy) or OLS models on the top and bottom halves of negative Black-White racial stereotypes, with 95% CIs. Models control on demographics, party, and ideology.

Political Moderators: Partisanship (PID) and Ideology (Ideo)

Tables A16-A20 present the political moderator results. Models include pre-treatment controls except ideology and partisanship, which are replaced with racial resentment, racial stereotypes, and White identity. Partisanship and ideology are coded with three categories (roughly corresponding to terciles). Dem. or Lib. is the baseline.

Table A16: Sympathy & anti-Black hypotheses (Equation 1, Baseline = Control), Political Moderators

	Treatment policy		Candidate		Taxes		Emotions	
	PID	Ideo	PID	Ideo	PID	Ideo	PID	Ideo
SW	1.542 (.585)	1.760 (.483)	0.030 (.031)	0.081 (.031)	0.011 (.035)	0.039 (.035)	0.016 (.023)	0.038 (.023)
SB	0.258 (.403)	0.593 (.359)	0.035 (.030)	0.056 (.030)	0.051 (.033)	0.108 (.033)	0.002 (.023)	0.047 (.022)
Rep. or Cons.	-1.462 (.346)	-0.765 (.342)	-0.163 (.032)	-0.130 (.034)	-0.061 (.036)	-0.007 (.038)	-0.054 (.025)	-0.039 (.025)
Ind. or Mod.	-1.290 (.457)	0.157 (.387)	-0.156 (.045)	0.032 (.038)	-0.084 (.051)	-0.007 (.042)	-0.045 (.034)	-0.016 (.028)
SW X Rep. or Cons.	-0.395 (.649)	-0.282 (.587)	0.082 (.043)	0.049 (.047)	0.033 (.048)	0.026 (.052)	0.026 (.033)	0.009 (.035)
SB X Rep. or Cons.	0.531 (.488)	0.309 (.490)	0.038 (.042)	0.031 (.046)	-0.041 (.047)	-0.116 (.052)	0.067 (.032)	0.011 (.035)
SW X Ind. or Mod.	-0.279 (.778)	-1.047 (.665)	0.074 (.061)	-0.068 (.053)	0.092 (.069)	-0.019 (.059)	0.041 (.046)	0.002 (.040)
SB X Ind. or Mod.	1.035 (.698)	-0.044 (.579)	0.066 (.065)	-0.042 (.053)	0.075 (.073)	-0.103 (.059)	0.045 (.049)	-0.026 (.040)
Const.	2.674 (.622)	2.166 (.631)	0.822 (.053)	0.774 (.055)	0.391 (.059)	0.377 (.061)	0.710 (.040)	0.715 (.041)
Obs.	860	805	860	805	860	805	857	802
Adj. R^2	--	--	0.308	0.312	0.203	0.225	0.126	0.142

Table A17: Racially selective sympathy hypothesis (Equation 2, Baseline = Sympathetic White), Political Moderators

	Treatment policy		Candidate		Taxes		Emotions	
	PID	Ideo	PID	Ideo	PID	Ideo	PID	Ideo
SB	-1.197 (.601)	-1.117 (.508)	0.011 (.030)	-0.018 (.032)	0.043 (.035)	0.079 (.036)	-0.013 (.024)	0.010 (.024)
Rep. or Cons.	-1.847 (.574)	-1.069 (.502)	-0.071 (.035)	-0.072 (.037)	-0.018 (.040)	0.028 (.043)	-0.030 (.027)	-0.036 (.028)
Ind. or Mod.	-1.554 (.642)	-0.897 (.547)	-0.086 (.044)	-0.032 (.038)	0.011 (.050)	-0.020 (.044)	-0.001 (.034)	-0.013 (.029)
SB X Rep. or Cons.	0.777 (.666)	0.463 (.615)	-0.057 (.043)	-0.033 (.047)	-0.078 (.049)	-0.156 (.054)	0.038 (.033)	-0.0004 (.036)
SB X Ind. or Mod.	1.237 (.836)	0.970 (.703)	-0.012 (.063)	0.016 (.053)	-0.024 (.073)	-0.097 (.061)	0.003 (.049)	-0.031 (.041)

Const.	4.182 (.949)	3.981 (.968)	0.872 (.065)	0.878 (.068)	0.420 (.075)	0.446 (.079)	0.723 (.051)	0.755 (.052)
Obs.	570	531	570	531	570	531	568	529
Adj. R^2	--	--	0.294	0.302	0.213	0.236	0.109	0.123

Table A18: Antipathy & pro-White hypothesis (Equation 3, Baseline = Control), Political Moderators

	Treatment policy		Candidate		Taxes		Emotions	
	PID	Ideo	PID	Ideo	PID	Ideo	PID	Ideo
UW	-0.504 (.369)	0.290 (.344)	-0.019 (.030)	0.020 (.030)	0.016 (.034)	0.027 (.034)	-0.068 (.024)	-0.056 (.024)
UB	-0.200 (.373)	0.138 (.330)	0.023 (.030)	0.035 (.030)	0.014 (.033)	0.047 (.033)	-0.042 (.024)	-0.041 (.023)
Rep. or Cons.	-1.366 (.346)	-0.716 (.340)	-0.176 (.032)	-0.135 (.034)	-0.080 (.036)	-0.012 (.038)	-0.031 (.025)	0.003 (.027)
Ind. or Mod.	-1.174 (.461)	0.204 (.389)	-0.137 (.045)	0.032 (.038)	-0.076 (.050)	-0.001 (.042)	-0.031 (.036)	-0.001 (.042)
UW X Rep. or Cons.	0.825 (.458)	0.122 (.480)	0.056 (.042)	0.009 (.047)	-0.020 (.047)	-0.037 (.052)	0.048 (.033)	0.073 (.037)
UB X Rep. or Cons.	0.469 (.461)	0.313 (.466)	0.011 (.042)	0.037 (.046)	-0.004 (.047)	-0.033 (.051)	0.005 (.033)	0.022 (.036)
UW X Ind. or Mod.	1.386 (.656)	-0.449 (.555)	0.124 (.062)	-0.025 (.053)	-0.027 (.070)	-0.026 (.059)	0.043 (.049)	-0.015 (.042)
UB X Ind. or Mod.	0.927 (.654)	-0.528 (.546)	0.009 (.063)	-0.082 (.054)	0.007 (.071)	-0.080 (.060)	0.020 (.050)	-0.014 (.042)
Const.	2.347 (.554)	1.631 (.549)	0.840 (.051)	0.777 (.053)	0.365 (.058)	0.320 (.059)	0.734 (.041)	0.746 (.042)
Obs.	866	815	867	816	866	815	865	814
Adj. R^2	--	--	0.311	0.304	0.192	0.200	0.155	0.169

Table A19: Racial antipathy hypothesis (Equation 4, Baseline = Unsympathetic White), Political Moderators

	Treatment policy		Candidate		Taxes		Emotions	
	PID	Ideo	PID	Ideo	PID	Ideo	PID	Ideo
UB	0.316 (.354)	-0.179 (.343)	0.040 (.030)	0.013 (.031)	-0.004 (.034)	0.017 (.035)	0.024 (.025)	0.015 (.025)
Rep. or Cons.	-0.504 (.348)	-0.638 (.358)	-0.123 (.034)	-0.127 (.036)	-0.096 (.040)	-0.049 (.041)	0.023 (.028)	0.084 (.029)
Ind. or Mod.	0.273 (.483)	-0.234 (.400)	-0.014 (.044)	0.006 (.038)	-0.108 (.051)	-0.035 (.043)	0.019 (.037)	-0.002 (.031)
UB X Rep. or Cons.	-0.367 (.447)	0.250 (.473)	-0.039 (.042)	0.029 (.046)	0.013 (.048)	0.006 (.053)	-0.040 (.034)	-0.050 (.038)
UB X Ind. or Mod.	-0.433 (.677)	-0.050 (.550)	-0.108 (.063)	-0.053 (.054)	0.053 (.072)	-0.047 (.061)	-0.022 (.052)	0.004 (.043)
Const.	1.677 (.672)	1.715 (.702)	0.861 (.064)	0.829 (.067)	0.405 (.074)	0.358 (.077)	0.664 (.053)	0.692 (.055)
Obs.	576	541	577	542	576	541	576	541

Adj. R^2	--	--	0.308	0.293	0.196	0.198	0.156	0.175

Table A20: Racial main effect hypothesis (Equation 7, Baseline = Pooled White), Political Moderators

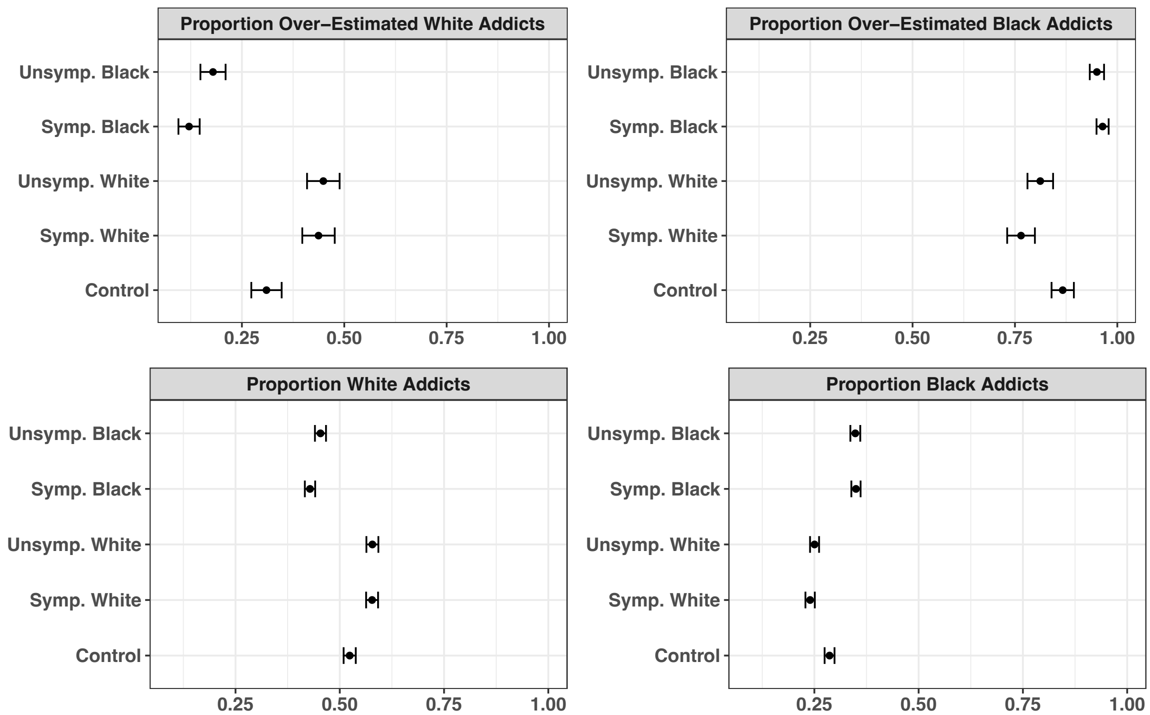
	Treatment policy		Candidate		Taxes		Emotions	
	PID	Ideo	PID	Ideo	PID	Ideo	PID	Ideo
Pooled Black	-0.174 (.284)	-0.453 (.271)	0.023 (.021)	-0.008 (.022)	0.021 (.024)	0.045 (.025)	0.006 (.017)	0.015 (.018)
Rep. or Cons.	-0.853 (.269)	-0.628 (.273)	-0.091 (.025)	-0.099 (.026)	-0.055 (.028)	-0.012 (.029)	0.001 (.020)	0.035 (.021)
Ind. or Mod.	-0.264 (.348)	-0.377 (.303)	-0.045 (.031)	-0.019 (.027)	-0.040 (.035)	-0.027 (.030)	0.010 (.025)	0.0002 (.022)
Pooled Black X Rep. or Cons.	-0.028 (.340)	0.154 (.353)	-0.047 (.030)	0.002 (.033)	-0.036 (.034)	-0.073 (.038)	-0.002 (.024)	-0.031 (.027)
Pooled Black X Ind. or Mod.	0.123 (.489)	0.260 (.412)	-0.060 (.045)	-0.011 (.038)	0.005 (.051)	-0.070 (.043)	-0.007 (.036)	-0.017 (.030)
Const.	2.625 (.515)	2.610 (.543)	0.874 (.046)	0.870 (.048)	0.414 (.052)	0.404 (.054)	0.707 (.037)	0.735 (.039)
Obs.	1,146	1,072	1,147	1,073	1,146	1,072	1,144	1,070
Adj. R^2	--	--	0.290	0.292	0.206	0.219	0.127	0.137

A.7 Complier average causal effect

Some respondents may have firm ideas about the racial composition of opioid users and may not update these beliefs after exposure to treatment. Average treatment effects may therefore be biased towards the null. As a robustness check, we calculated the complier average causal effect (CACE). Compliers include respondents assigned to Black treatments who over-estimate the Black percentage of opioid addicts, and those assigned to the White treatments who over-estimate the White percentage of addicts.[5] We expect stronger effects among compliers.

Figure A7 presents observed compliance means and offers evidence of compliance. As evident in the top-left panel, over-estimates of White opioid addicts are highest in the White conditions and lowest in the Black conditions (one-tailed, $p < 0.001$ and 0.002, respectively).[6] The top-right panel shows the expected pattern for over-estimating Black percentages (for all, one-tailed, $p < 0.001$).[7] For descriptive purposes, raw proportions (rather than over-estimates) are in the bottom panels.[8]

Figure A7: Observed compliance means across experimental conditions (raw values, 83% CIs)



[5] This measures uses the same question on racial composition of opioid addicts described in the main paper. We also preregistered a looser measure of compliance as a robustness check. It includes as compliers those who underestimate the percentages of White or Black addicts by up to 10%. Compliance values are unchanged for this measure, so the CACE estimates would be unchanged.

[6] Proportion over-estimated White addicts: 0.443 (0.020) for pooled White and 0.150 (0.014) for pooled Black conditions.

[7] Proportion over-estimated Black addicts: 0.788 (0.017) for pooled White and 0.957(0.008) for pooled Black conditions.

[8] Raw proportion estimated White addicts: 0.578 (0.007) for pooled White and 0.441 (0.007) for pooled Black conditions. Raw proportion estimated Black addicts: 0.245 (0.006) for pooled White and 0.349 (0.006) for pooled Black conditions.

Next, we calculate the CACE estimates for the racial main effect (comparing pooled Black and White conditions). Compliance is a binary indicator for over-estimating the percentage of Black addicts (or not). We regress this on an indicator for pooled Black (White) conditions. In the second stage, we regress each outcome on instrumented compliance. Compared to the average treatment effects on the full sample, the racial main effect on compliers is larger on policy, though similarly not statistically significant at 0.05. The CACE on the other outcomes are similar to the ATE.[9] We repeat this for the racially selective sympathy hypothesis (comparing sympathetic Black and White conditions). The CACE effects are larger than the ATEs on policy and candidate support, though only the policy CACE reaches the 0.05 level.[10] We find a similar pattern of results using over-estimates of White addicts, for both hypotheses.[11]

In sum, the racial treatment effects are particularly large among compliers, but not consistently. Black frames generate less support than White frames only on policy and candidates. The racial treatment effects are statistically significant only for policy and only from sympathetic treatments. Thus, perceiving a disproportionate racial impact of the opioid crisis helps explain the effect of the racially selective sympathy frame. The racially selective sympathy CACE was not preregistered.

[9] Specifically, the marginal effects and standard errors are -0.270 (0.154) for policy, -0.043 (0.088) for candidate, 0.066 (0.100) for taxes, and 0.026 (0.071) for emotions. The first and second stage each uses OLS with standard controls.

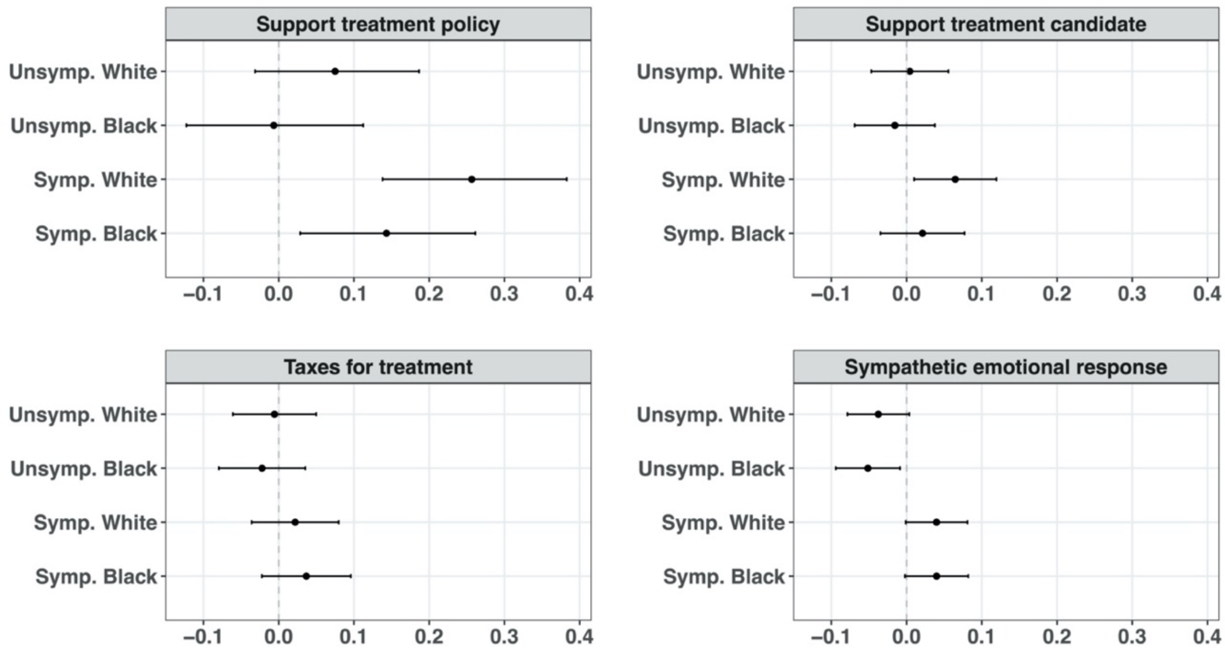
[10] We replace the indicator for pooled Black (White) conditions with an indicator for sympathetic Black (White). The marginal effects and standard errors are -0.395 (0.171) for policy, -0.101 (0.101) for candidate, 0.063 (0.116) for taxes, and 0.023 (0.076) for emotions. The effect on policy may be inflated because of the skewed distribution of Black over-estimates and the binary outcome variable.

[11] Compared to the ATEs in the full sample, the racial main effect estimates for compliers are larger for policy and candidate, though similarly not statistically significant at the 0.05 level. Specifically, the marginal effects and standard errors are 0.162 (0.092) for policy, 0.026 (0.052) for candidate, -0.040 (0.060) for taxes, and -0.016 (0.042) for emotions. The racially selective sympathy effects on compliers are also larger for policy and candidate, although only the former is statistically significant at the 0.05 level. The marginal effects and standard errors are 0.262 (0.112) for policy, 0.067 (0.067) for candidate, -0.042 (0.077) for taxes, and -0.015 (0.050) for emotions.

A.8 News exposure

Prior news exposure may depress treatment effects. If so, we would see stronger effects among respondents who follow opioid news "Not too closely" or "Not closely at all" (n = 891), relative to the full sample. Figure A8 presents the effects of each treatment relative to the control, for this subset. The racial main effect on policy is stronger among respondents with low prior opioid news exposure, a group less likely to have already been “treated” (White - Black = 10 points, $p < 0.05$). Overall, these results are very similar in magnitude and statistical significance to the full sample shown in Figure 1.

Figure A8: Comparing each treatment to no-story control (Low news exposure respondents)



Estimates are based on logit and OLS models with 95% CIs. Models control on demographics, party, and ideology

A.9 References

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