The Political Effects of Opioid Addiction Frames
Supplementary Appendix

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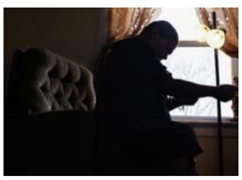
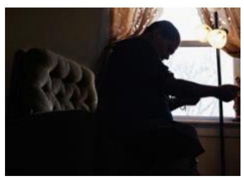
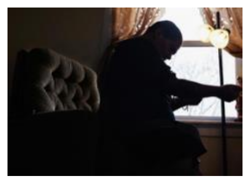
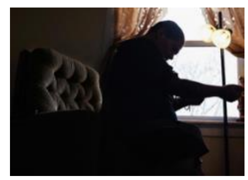
A.1 Experimental conditions: Contents

To heighten realism and create strong, distinct treatments, we incorporated multiple cues of valence and race. Bolded text indicates differences across treatments.

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
			
Since 1999, almost four hundred thousand Americans have died from overdoses related to opioids. The most recent figures from the Centers for Disease Control and Prevention suggest that one hundred and thirty Americans die every day from opioid overdoses.	Since 1999, almost four hundred thousand Americans have died from overdoses related to opioids. The most recent figures from the Centers for Disease Control and Prevention suggest that one hundred and thirty Americans die every day from opioid overdoses.	Since 1999, almost four hundred thousand Americans have died from overdoses related to opioids. The most recent figures from the Centers for Disease Control and Prevention suggest that one hundred and thirty Americans die every day from opioid overdoses.	Since 1999, almost four hundred thousand Americans have died from overdoses related to opioids. The most recent figures from the Centers for Disease Control and Prevention suggest that one hundred and thirty Americans die every day from opioid overdoses.
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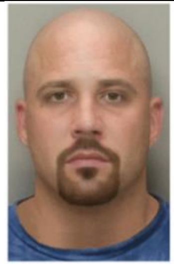
say these are 'deaths of **despair'.** Over the years, many medical professionals said that opioid addiction is **not** a serious danger. They **encouraged** patients prescribed opioids like OxyContin to use these for pain **from an ever-wider range of maladies.** **Sales representatives** disregarded 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.’”	problem. **“I realized I** have to look at myself. I told them ‘I have a problem.’”	**want to** have to look at myself. I told them ‘I **don’t** have a problem.’”	**want to** have to look at myself. I told them ‘I **don’t** 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.	**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.	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.**	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 **tried** quitting heroin, “but **even though you desperately want to stop,** you just **can’t ”** he said. He started injecting it.	He **tried** quitting heroin, “but **even though you desperately want to stop,** you just **can’t ”** he said. He started injecting it.	He **thought about** quitting heroin, “but you just **don’t feel like stopping ,”** he said. He started injecting it.	He **thought about** quitting heroin, “but you just **don’t feel like stopping,”** 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.	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.	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.	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 **was ashamed.**	When he was evicted, he **was ashamed.**	When he was evicted, he **started defecating in the street.**	When he was evicted, he **started defecating in the street.**
He **couldn’t stand the idea that** the neighbors **would** stop letting their kids play outside so they wouldn’t see him using.	**He couldn’t stand the idea that** the neighbors **would** stop letting their kids play outside so they wouldn’t see him using.	The neighbors stopped letting their kids play outside so they wouldn’t see him using.	The neighbors stopped letting their kids play outside so they wouldn’t see him using.
Mike **checked into** a treatment program.	Mike **checked into** a treatment program.	Mike **knew he should check into** a treatment program.	Mike **knew he should check 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.	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.	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.	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 + $b1_1$SW + $b2_1$SB [C baseline]
  - Tests: Sympathy and Anti-Black hypotheses
- Equation 2: DV = a + $b1_2$SB [SW baseline]
  - Tests: Racial sympathy hypothesis
- Equation 3: DV = a+ $b1_3$UW +$b2_3$UB [C baseline]
  - Tests: Antipathy and Pro-White bias hypotheses
- Equation 4: DV = a+ $b1_4$UB [UW baseline]
  - Tests: Racial antipathy hypothesis
- Equation 5: DV = a+ $b1_5$SW [UW baseline]
  - Tests: Full valence hypothesis
- Equation 6: DV = a + $b1_6$SB [UB baseline]
  - Tests: Full valence hypothesis
- Equation 7: DV = a + $b1_7$(SB + UB) [(SW + UW) baseline]
  - Tests: Racial main effect hypothesis

A.3 Emotional outcomes, Dynata study

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

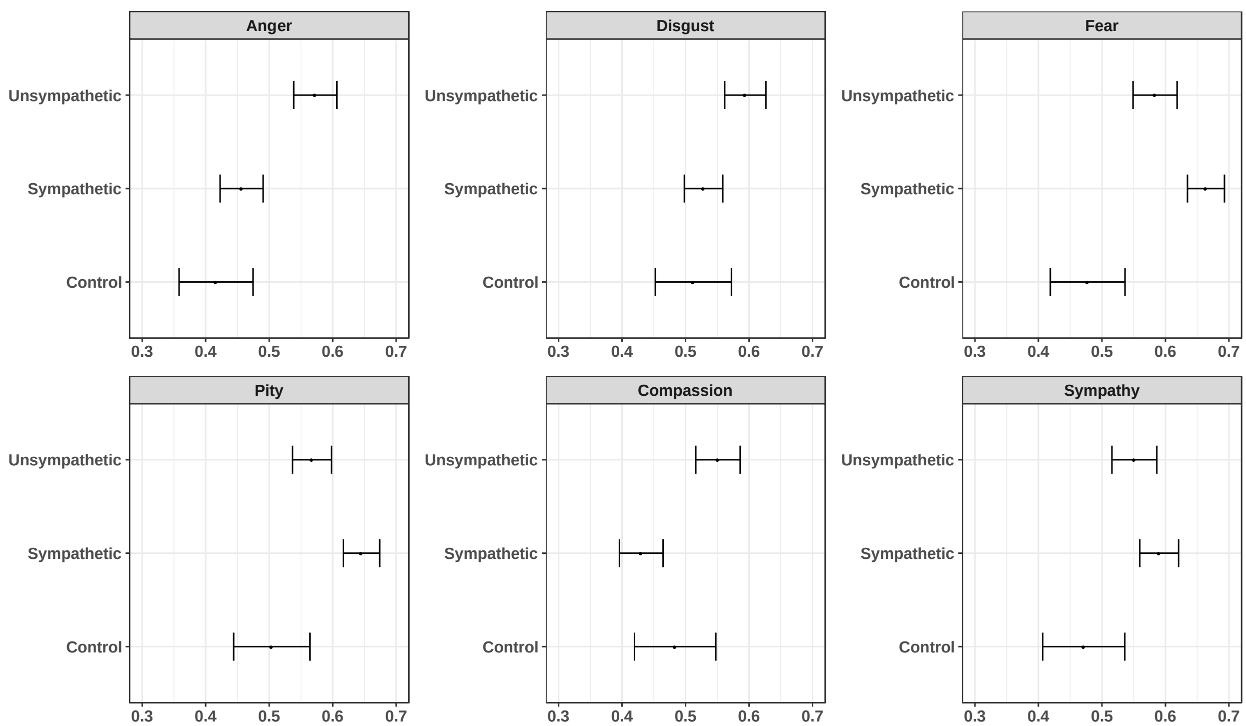
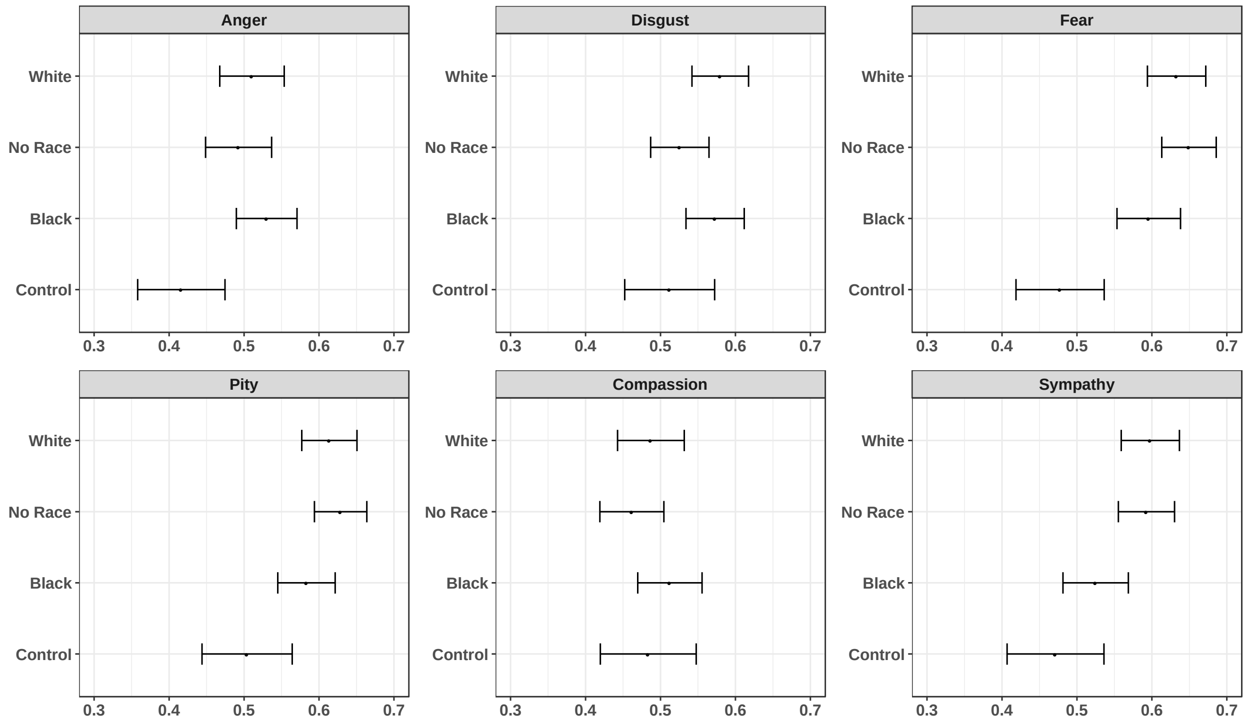


Figure A3: Mean emotional responses to 'drug addicts', by racial condition (Dynata, 83% CIs)



A.4 Manipulation checks, main sample

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)

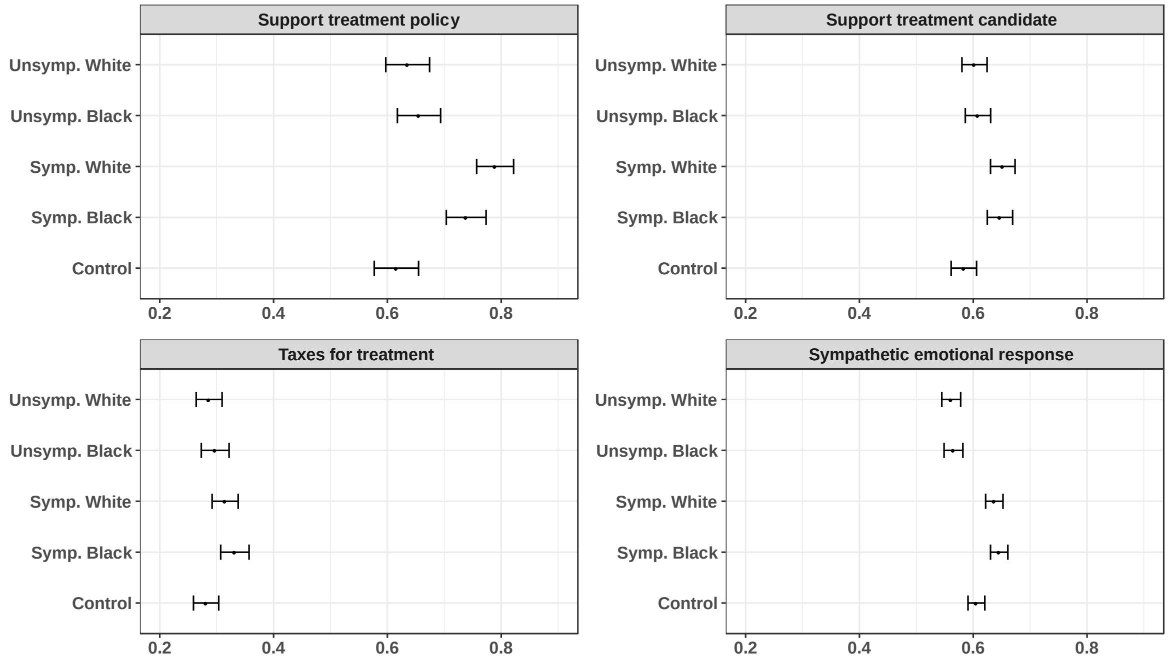
	Sympathy for Mike (OLS)	
	(1)	(2)
Pooled Sympathetic	0.186	0.194
	(.016)	(.016)
Const.	0.452	0.605
	(.012)	(.054)
Controls	N	Y
Obs.	1,213	1,079
Adj. R^2	0.097	0.170

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 A4: Mean outcome values across experimental conditions (raw values, 83% CIs)



A.6 Regression tables, main study

"Treatment policy" is a binary variable modeled with logistic regression. Remaining outcomes are modeled with OLS. Variables are defined in the paper. Entries are logit coefficients for treatment policy and OLS for the rest, with standard errors in parentheses.

A.6.1 Main effects

Tables A3-A9 report results for Figures 2-4. Even-numbered columns include pre-treatment controls: age, region, education, gender, income, partisanship, and ideology. Odd-numbered columns omit controls.

Table A3: 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 A4: Racial 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 A5: 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 A6: 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 A7: 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 A8: 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	1.398	0.608	0.819	0.297	0.447	0.565	0.687
	(.121)	(.641)	(.016)	(.069)	(.018)	(.080)	(.011)	(.054)
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 A9: 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	2.355	0.627	0.916	0.301	0.412	0.599	0.715
	(.090)	(.499)	(.011)	(.050)	(.012)	(.057)	(.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 Stereotype (RS) and White Identity (WI)

Tables A10-A14 present racial predisposition interaction results. All models include the standard pre-treatment controls. Racial resentment and White identity are divided into terciles and included as indicator variables, with the low tercile as the omitted baseline. Racial stereotype is an indicator variable coded with a median split. Each column includes a different racial moderator. Entries are logit coefficients for treatment policy and OLS for the rest, with standard errors in parentheses.

Table A10: 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	-0.203	0.270	-0.19	-0.046	0.051	-0.202	-0.041	0.053	-0.118	-0.101	-0.037
	(.427)	(.358)	(.327)	(.039)	(.038)	(.033)	(.044)	(.043)	(.037)	(.030)	(.028)	(.025)
Mid RP	-0.760	--	0.371	-0.078	--	0.031	-0.12	--	0.032	-0.073	--	-0.029
	(.404)		(.387)	(.036)		(.039)	(.041)		(.044)	(.028)		(.029)
SW X High RP	0.258	0.489	0.032	0.058	-0.004	-0.048	0.019	-0.001	-0.051	0.048	0.027	-0.014
	(.695)	(.516)	(.495)	(.048)	(.051)	(.047)	(.055)	(.059)	(.053)	(.037)	(.038)	(.035)
SB X High RP	-0.908	-0.550	-0.490	-0.065	0.0003	-0.026	-0.093	0.011	0.023	0.005	-0.025	-0.038
	(.748)	(.516)	(.481)	(.048)	(.054)	(.047)	(.055)	(.061)	(.053)	(.037)	(.039)	(.035)
SW X Mid RP	-0.553	--	-0.037	-0.043	--	-0.096	0.027	--	0.005	-0.017	--	-0.047
	(.718)		(.643)	(.050)		(.057)	(.057)		(.065)	(.038)		(.042)
SB X	-0.908	--	-0.524	-0.029	--	-0.018	-0.021	--	-0.019	0.015	--	-0.027

Mid RP	(.762)		(.570)	(.049)		(.055)	(.056)		(.063)	(.038)		(.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 A11: 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 A12: 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	-0.488	--	0.331	-0.071	--	0.012	-0.002	--	0.042	0.023	--	0.054

Mid RP	(.586)		(.603)	(.050)		(.059)	(.057)		(.066)	(.041)		(.047)
UB X	-0.775	--	0.536	-0.064	--	0.005	-0.008	--	0.054	-0.029	--	0.056
Mid RP	(.602)		(.565)	(.049)		(.056)	(.055)		(.064)	(.040)		(.045)
Const.	1.889	2.072	1.737	0.844	0.879	0.844	0.328	0.345	0.307	0.701	0.720	0.727
	(.585)	(.526)	(.554)	(.055)	(.054)	(.057)	(.062)	(.061)	(.064)	(.044)	(.043)	(.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 A13: 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	0.117	-0.268	0.012	0.013	0.016	0.025	0.002	0.023	0.037	0.006	-0.019
	(.539)	(.220)	(.306)	(.035)	(.023)	(.034)	(.041)	(.027)	(.039)	(.029)	(.019)	(.028)
High RP	-2.164	0.365	0.078	-0.225	0.028	0.037	-0.233	-0.018	0.011	-0.140	-0.053	-0.057
	(.457)	(.365)	(.311)	(.039)	(.041)	(.034)	(.045)	(.046)	(.039)	(.032)	(.033)	(.028)
Mid RP	-1.509	--	0.658	-0.156	--	0.043	-0.138	--	0.069	-0.061	--	0.015
	(.460)		(.458)	(.039)		(.045)	(.045)		(.051)	(.033)		(.037)
U.B. X	-0.282	-1.080	0.476	-0.013	-0.016	-0.001	-0.037	0.057	-0.030	-0.056	-0.025	0.049
High RP	(.619)	(.526)	(.437)	(.049)	(.058)	(.048)	(.056)	(.067)	(.054)	(.041)	(.048)	(.039)
U.B. X	-0.177	--	0.148	0.008	--	-0.008	-0.005	--	0.014	-0.050	--	0.003
Mid RP	(.639)		(.606)	(.052)		(.060)	(.059)		(.068)	(.043)		(.049)
Const.	1.958	1.851	1.647	0.900	0.909	0.885	0.344	0.365	0.336	0.632	0.662	0.664
	(.733)	(.667)	(.680)	(.068)	(.070)	(.073)	(.079)	(.081)	(.083)	(.057)	(.058)	(.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 A14: 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	-0.700	-1.092	0.069	-0.071	-0.009	0.023	-0.077	0.031	0.029	-0.053	-0.046	0.023
X High RP	(.489)	(.362)	(.321)	(.034)	(.039)	(.034)	(.039)	(.045)	(.038)	(.028)	(.031)	(.027)
Pooled Black	-0.314	--	-0.141	0.008	--	0.045	-0.026	--	-0.004	-0.012	--	0.022
X Mid RP	(.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

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

Tables A15-A19 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 A15: 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 A16: 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 A17: Equation 3 (Baseline = Control), Political Moderators

	Treatment policy		Candidate		Taxes		Emotions	
	PID	Ideo	PID	Ideo	PID	Ideo	PID	Ideo
UW	-0.504	0.290	-0.019	0.020	0.016	0.027	-0.068	-0.056
	(.369)	(.344)	(.030)	(.030)	(.034)	(.034)	(.024)	(.024)
UB	-0.200	0.138	0.023	0.035	0.014	0.047	-0.042	-0.041
	(.373)	(.330)	(.030)	(.030)	(.033)	(.033)	(.024)	(.023)
Rep. or Cons.	-1.366	-0.716	-0.176	-0.135	-0.080	-0.012	-0.031	0.003
	(.346)	(.340)	(.032)	(.034)	(.036)	(.038)	(.025)	(.027)
Ind. or Mod.	-1.174	0.204	-0.137	0.032	-0.076	-0.001	-0.031	-0.001
	(.461)	(.389)	(.045)	(.038)	(.050)	(.042)	(.036)	(.042)
UW X Rep. or Cons.	0.825	0.122	0.056	0.009	-0.020	-0.037	0.048	0.073
	(.458)	(.480)	(.042)	(.047)	(.047)	(.052)	(.033)	(.037)
UB X Rep. or Cons.	0.469	0.313	0.011	0.037	-0.004	-0.033	0.005	0.022
	(.461)	(.466)	(.042)	(.046)	(.047)	(.051)	(.033)	(.036)
UW X Ind. or Mod.	1.386	-0.449	0.124	-0.025	-0.027	-0.026	0.043	-0.015
	(.656)	(.555)	(.062)	(.053)	(.070)	(.059)	(.049)	(.042)
UB X Ind. or Mod.	0.927	-0.528	0.009	-0.082	0.007	-0.080	0.020	-0.014
	(.654)	(.546)	(.063)	(.054)	(.071)	(.060)	(.050)	(.042)
Const.	2.347	1.631	0.840	0.777	0.365	0.320	0.734	0.746
	(.554)	(.549)	(.051)	(.053)	(.058)	(.059)	(.041)	(.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 A18: Equation 4 (Baseline = Unsympathetic White), Political Moderators

	Treatment policy		Candidate		Taxes		Emotions	
	PID	Ideo	PID	Ideo	PID	Ideo	PID	Ideo
UB	0.316	-0.179	0.040	0.013	-0.004	0.017	0.024	0.015
	(.354)	(.343)	(.030)	(.031)	(.034)	(.035)	(.025)	(.025)
Rep. or Cons.	-0.504	-0.638	-0.123	-0.127	-0.096	-0.049	0.023	0.084
	(.348)	(.358)	(.034)	(.036)	(.040)	(.041)	(.028)	(.029)
Ind. or Mod.	0.273	-0.234	-0.014	0.006	-0.108	-0.035	0.019	-0.002
	(.483)	(.400)	(.044)	(.038)	(.051)	(.043)	(.037)	(.031)
UB X Rep. or Cons.	-0.367	0.250	-0.039	0.029	0.013	0.006	-0.040	-0.050
	(.447)	(.473)	(.042)	(.046)	(.048)	(.053)	(.034)	(.038)
UB X Ind. or Mod.	-0.433	-0.050	-0.108	-0.053	0.053	-0.047	-0.022	0.004
	(.677)	(.550)	(.063)	(.054)	(.072)	(.061)	(.052)	(.043)
Const.	1.677	1.715	0.861	0.829	0.405	0.358	0.664	0.692
	(.672)	(.702)	(.064)	(.067)	(.074)	(.077)	(.053)	(.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 A19: 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.[1] We expect stronger effects among compliers.

Figure A5 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).[2] The top-right panel shows the expected pattern for over-estimating Black percentages (for all, one-tailed, $p < 0.001$).[3] For descriptive purposes, raw proportions (rather than over-estimates) are in the bottom panels.[4]

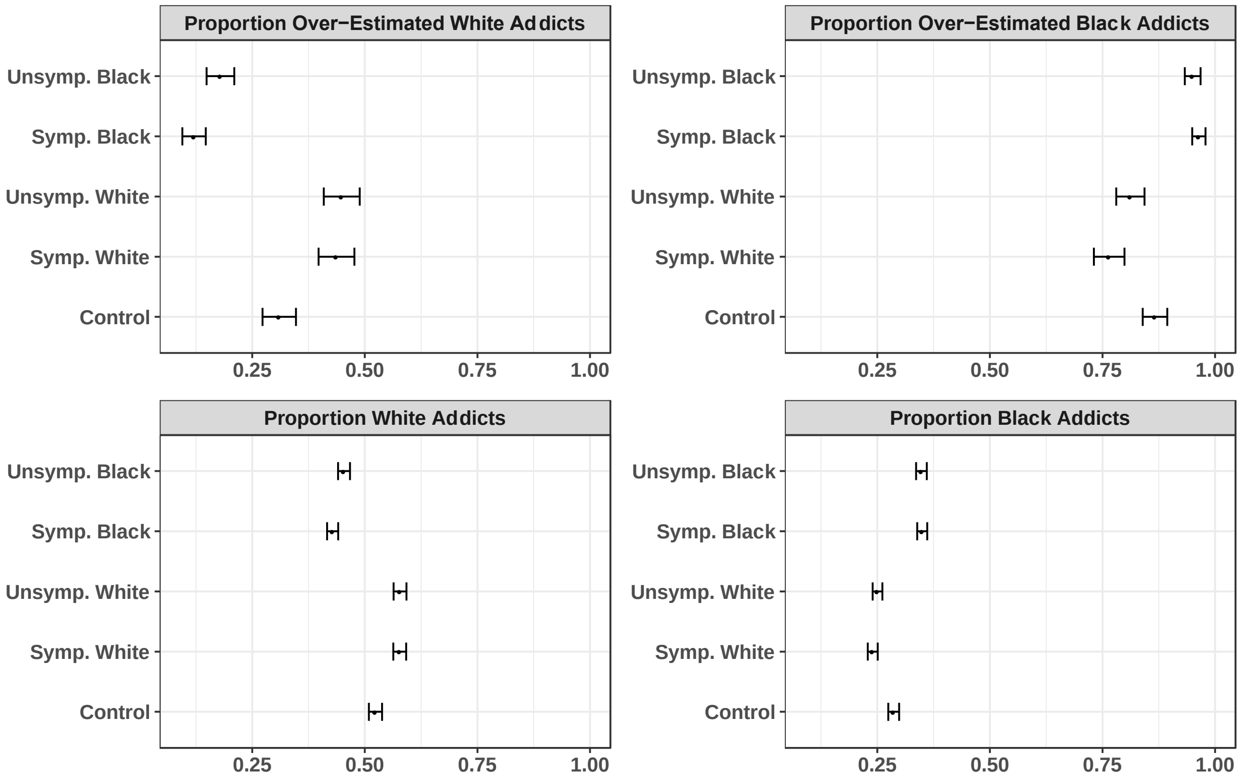
[1] This measures uses the same question on racial composition of opioid addicts described in the main paper. We also preregistered a looser measure of compliance as a robustness check. It includes as compliers those who underestimate the percentages of White or Black addicts by up to 10%. Compliance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

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

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

[4] 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.

Figure A5: Observed compliance means across experimental conditions (raw values, 83% CIs)



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.[5] We repeat this for the racial 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.[6] We find a similar pattern of results using over-estimates of White addicts, for both hypotheses.[7]

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[5] 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.

[6] 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 0.026 (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. The CACE analysis for racial sympathy was not pre-registered.

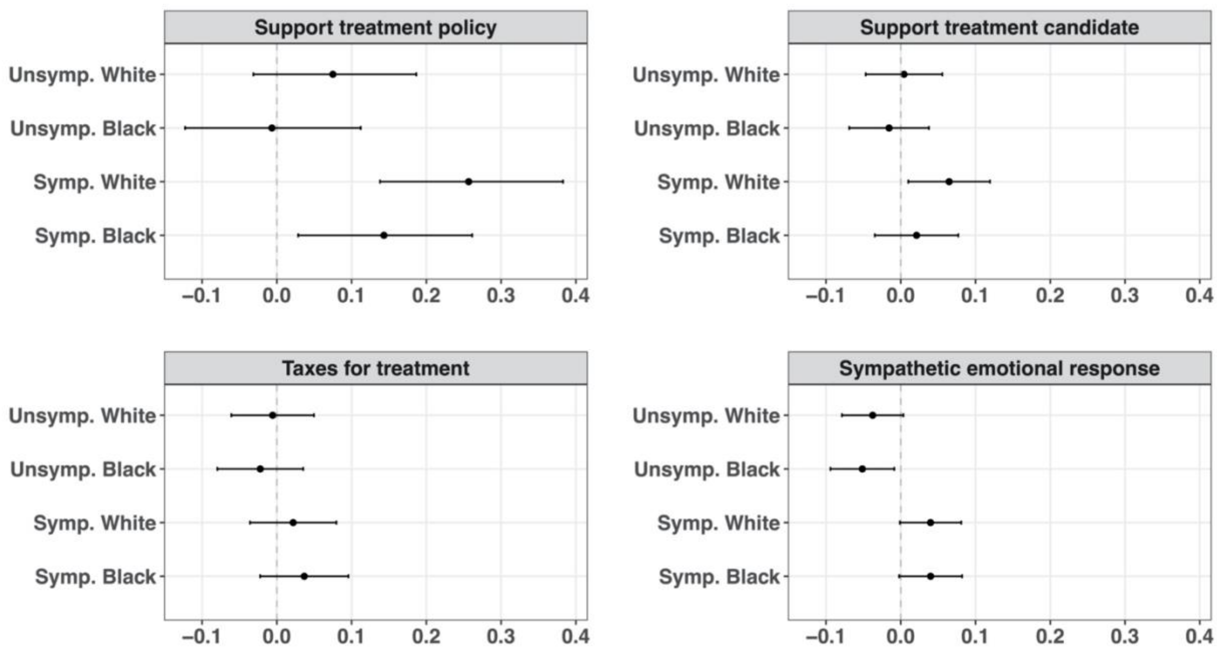
[7] Compared to the ATEs in the full sample, the racial main effect estimates for compliers are larger for policy and candidate, though similarly not statistically significant at the 0.05 level. Specifically, the

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.

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 A6 presents the effects of each treatment relative to the control, for this subset. These results are very similar in magnitude and statistical significance to the full sample shown in Figure 2.

Figure A6: 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.

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 racial 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.