Structural Analysis of Xenophobia

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December 22, 2021

Abstract

We estimate a signaling game of xenophobic behaviors to understand how individual racial animus and perceived unacceptance of racial animus determine xenophobic behaviors in equilibrium. To identify our model, we design a survey about anti-Chinese xenophobia in the US during the Pandemic. We validate our estimates by comparing our model predictions with the causal estimates obtained from the information Randomized Controlled Trial. We find raising perceived unacceptance is more effective than reducing racial animus at decreasing most xenophobic behaviors. We quantify the effects of a COVID infection and Fox News viewership on xenophobic behaviors in the short and long run.

JEL Classification: J15, Z13, Z18

Keywords : racial animus, perceived unacceptance, xenophobia, Sinophobia, COVID-19

*hdeng10@jhu.edu, yujungghwang@gmail.com. Our survey is registered at the AEA registry with ID AEARCTR-0006365 and it was approved by the Homewood IRB (Study Number : HIRB00011673). We thank Filipe Campante for reading our paper many times and giving insightful suggestions. The authors thank many people who kindly reviewed our survey questionnaire or draft and provided help, including Jane Chen, Taha Choukmane, Matthew Hom, Louise Laage, Eunhee Lee, Lixiong Li, Tesary Lin, Mario Macis, Aureo de Paula, Yin Pan, Zhenyu Wang, Pengpeng Xiao, Hanna Wang, Fangzhu Yang, and Matthew V. Zahn. We thank the seminar participants at Johns Hopkins University, New York Fed, the University of Hawaii, and the University of Wisconsin-Madison for their comments. Also, we thank the Hopkins Population Center and Hopkins Business and Health Initiative for funding this project. All errors are our own.

1 Introduction

Many social interactions involve individuals displaying animosity towards members of a different group. One key feature of these interactions is that, while they contain a purely individual dimension – say, a personal dislike against individuals of a different race, religion, nationality, etc – they also have a social component: how others judge such animosity against a given group will affect one's propensity to express it. Understanding the interplay of these different dimensions is crucial for understanding its prevalence, and figuring out how policy can address it.

This paper studies this question empirically, in the context of xenophobia. Xenophobia is defined as dislike against foreign people, and is becoming more salient as international migration is increasing. Our model is built upon Bénabou and Tirole (2006) which provided an important theoretical framework to study general pro-social behavior with an emphasis on the equilibrium nature of reputational motivation. In their model, people make pro-social behavior to signal their (good) types and the equilibrium reputation depends on which type in the economy makes the pro-social behavior. Only a few papers so far structurally estimated the Bénabou and Tirole (2006)-type model (Butera et al. (2021), Chandrasekhar et al. (2018), Dubé et al. (2017)). There are several challenges in doing so : how to measure reputational motivation and how to achieve identification despite potential multiple equilibria. In this paper, we propose a new method to address these challenges and structurally estimate an equilibrium model of xenophobia. The discussion in our paper can be extended to other pro-social behavior, or signaling game models.

Our model can also answer the long-standing question on the theory behind xenophobic behaviors. Paluck et al. (2021) has done an ambitious meta analysis on 418 experiments reported in 309 manuscripts between 2007 and 2019, and raised a question at the end of the review – which theory can reconcile findings from multiple experimental studies.[1] For example, when many experimental studies find information intervention can decrease xenophobic behaviors while racial animus barely changes, which theory is consistent with these two findings? We provide a structural model to understand what drives marginal change in xenophobic behaviors. The insights provided in our paper can shed light on how to design an effective policy intervention.

In our model, an agent, characterized with own racial animus and perceived unacceptance of racial animus, decides whether to commit a xenophobic action. Two motivations underpin the xenophobic action decision. First, there is an intrinsic motivation – higher racial animus

[1] To quote, "prejudice reduction interventions often seem more successful at changing discriminatory behaviors than at reducing negative stereotypes or animus (Mousa (2020), Scacco and Warren (2018)). Suppose this pattern of results proves to be robust in subsequent research : What would this pattern imply theoretically?"(Paluck et al. (2021), p.553)

increases pleasure from a xenophobic action. Second, there is a reputational motivation – individual perceived unacceptance determines the perceived social cost of having high racial animus. Because racial animus is not observable to others, each agent uses a xenophobic action to signal own racial animus type. The reputational response that an individual receives is called stigma/honor - that is, the expected racial animus conditional on xenophobic action/inaction. Stigma and honor are determined in equilibrium, reflecting which racial animus type commits a xenophobic action in the economy.

There are two main challenges in estimating our model, and in general, Bénabou and Tirole (2006)-type signaling game model : (i) measurement of motivations, that are labeled as racial animus and perceived unacceptance in our model, and (ii) presence of potential multiple equilibria. We model racial animus and perceived unacceptance as latent variables, and identify them using multiple proxy variables for each (Cunha et al. (2010)). In particular, we could not find survey questions for perceived unacceptance, so we develop a set of survey instruments with high internal validity. For racial animus, we use an established battery of questions from social psychology literature (Stephan et al. (1999))[2].

The second challenge is that our model exhibits multiple equilibria, which brings difficulty to both identification and estimation. For identification, we show that the structural parameters can be point-identified using our survey data and the sequential estimation strategy we propose as long as we know which part of data was generated from a single equilibrium (Proposition 1). We assume that our entire data was generated from a single equilibrium, for which we find supportive evidence[3]. For estimation, we do not need a further assumption on equilibrium selection : if there are multiple equilibria in data, which we find true in our data, our identification result implies that only one of them can fit our data. In the counterfactual analysis, we select an equilibrium in which the reputational gain, defined as stigma minus honor, is closest to the baseline level.

To corroborate our structural estimation, we implemented an information Randomized Controlled Trial (RCT) to generate exogenous variations to validate our structural estimation results. We compare the model predictions with the causal estimates obtained from the information Randomized Controlled Trial (RCT).[4] We confirm that our structural model with estimated parameters can replicate the causal estimates.

Our model is estimated using our survey data on anti-Chinese xenophobia in the US dur-

[2]The original questions are about Asian Americans. We replace the word Asian Americans with Chinese immigrants.

[3]We can not test every possibility of how different subsets of our data were generated from different equilibria. However, we try a plausible one – data from each US region was generated from different equilibria. And we find little evidence that these equilibria are statistically different.

[4]The information treatment is the one-minute video about how the pandemic is changing the Americans' perceptions of China and Chinese immigrants to a treated group. You can watch the video at the following url. https://www.youtube.com/watch?v=8sjOWt6PWdA

ing the COVID-19 pandemic. Our survey is an online panel survey and to ensure high-quality survey responses, we followed the state-of-the-art conventions in the literature : we worded our survey carefully to avoid selective participation by attitude toward Chinese immigrants, to induce efforts from participants to provide honest and accurate responses, to screen out inattentive participants, and to prevent social desirability bias, surveyor demand effect, and order effect. We collected 2363 survey responses from non-Asians living in the US, aged between 18 and 70 years old. Our sample is stratified along gender, race, education, age, marital status, and income.

Our measures for xenophobic behaviors include support for discriminatory institutions and outcomes from dictator games. Support for discriminatory institutions is measured by hypothetical questions about whether to donate to a Sinophobic organization and whether to sign a Sinophobic petition[5]. We argue that it is crucial to study these behaviors because such supports can be contagious to average people since they do not comprise a hate crime nor outlaw but still make it extremely difficult for Chinese immigrants to live in the US. Next, we implemented dictator games – money splitting games – to measure altruism toward a Chinese immigrant relative to White Americans.[6] The games were incentivized with monetary compensation, with the maximum amount close to the base participation payment. If a respondent shares more money with a White American than with a Chinese immigrant, we code such behavior as xenophobic.

Using our estimated model, we present three main counterfactual analysis. First, we find raising perceived unacceptance is more effective than suppressing racial animus at reducing most xenophobic behaviors we consider.[7] To see this, we shift racial animus and perceived unacceptance distribution by 0.13 standard deviations each. The 0.13 standard deviation is the difference between the most hostile racial group, White, and the most friendly group, other race (that is, non-White, non-Black, and non-Asian). Then, we compare the predicted xenophobic behaviors using our structural parameter estimates. We find much bigger decrease in xenophobic behaviors when we shift the perceived unacceptance.

We propose two reasons why shifting perceived unacceptance appears to be more effective than shifting racial animus in our counterfactual analysis. First, the marginal change in equilibrium depends on the mass of marginal agents, which in turn depends on the distributional shapes of racial animus and perceived unacceptance, as well as the current position

[5]Some research projects have asked survey participants whether to donate *real* money to different organizations and whether to sign a *real* petition (Bursztyn et al. (2020), Grigorieff et al. (2018), Elías et al. (2019)). This was not feasible because our institution's Institutional Review Board does not allow making any real political action for research.

[6]Dictator game outcomes are widely used in the literature as proxies for altruism toward a minority group (Bertrand and Duflo (2017)).

[7]The only exception is the outcome from a dictator game, whose relative importance parameter for perceived unacceptance is estimated to be smallest, and for which reducing racial animus is marginally more effective than increasing perceived unacceptance.

of the separating hyperplane to determine xenophobic behaviors. The estimated distribution of racial animus is highly skewed to the right, so there is a thin tail of the extreme haters, many of whom engage in xenophobic behaviors. The perceived unacceptance, on the other hand, is symmetrically distributed with more mass around the median. In our survey data, a small number of people between 9% and 23% engage in xenophobic behavior, and the current position of the hyperplane and the distributional shapes imply that more marginal agents will opt out from xenophobic behaviors when shifting along perceived unacceptance. This is the first-order effect after shifting each marginal distribution. Second, there is a second-order effect through changing reputational gain in equilibrium. A much larger increase in reputational gain occurs when the distribution of perceived unacceptance is shifted. Therefore, the reputational motivation causes marginal people with high perceived unacceptance to refrain from xenophobic behaviors.

The second counterfactual we consider is the effect of COVID (self) infection and we find an optimistic result: COVID (self) infection increases xenophobic behaviors in the short run but not in the long run.[8] To make counterfactual predictions, we first estimate how COVID (self) infection shifts the distribution of racial animus and perceived unacceptance using quantile regressions. To control for the potential endogeneity in COVID (self) infection, we control for a state fixed effect and extensive proxies for pre-pandemic attitude toward Chinese immigrants.[9] We assume that whether a respondent got infected with coronavirus is independent from unobservables that affect racial animus and perceived social unacceptance (at the time of our survey) under our extensive baseline controls. Next, we predict using our structural parameter estimates how the equilibrium will change. Our short run prediction assumes that the reputational gain is fixed at the baseline level and our long run prediction updates the reputational gain to a new level consistent with new aggregate behaviors. We find the COVID (self) infection polarizes the racial animus, shown by more mass at the tails. The shift in the distribution leads to increase in xenophobic behaviors in the short run. However, in the long run, it reduces xenophobic behaviors because the reputational gain from not making a xenophobic action increases so drastically. In a new equilibrium, xenophobic behaviors signal for much higher racial animus because the pandemic increased the number of extreme haters who newly engage in xenophobic behaviors. The moderate haters then decide to quit xenophobic behaviors to avoid the additional stigma caused by the more extreme actors.

The third counterfactual we conduct is the effect of watching Fox News. Following the same strategy as in the second counterfactual analysis, we first estimate how watching Fox

[8]COVID (self) infection is the only factor among various COVID-related experiences – including job loss – that significantly changes any motivation for xenophobic behaviors.

[9]The proxies include whether the respondent voted for Donald Trump in the presidential election in year 2016, the number of the person's close Asian friends, whether a spouse is an Asian, and Asian composition in childhood schools (primary, secondary, high school, and college). In addition, we control for demographic variables.

news shifts the distribution of racial animus and perceived unacceptance while controlling for a state fixed effect, and the proxies for the pre-pandemic attitudes toward Chinese immigrants as well as demographic variables. That is, we rely on a conditional independence assumption – Fox News viewership is independent of potential outcomes conditional on included controls.[10] If the conditional independence assumption is violated, our estimates will include a selection bias from the residual not explained by our extensive covariates.[11] Under our identifying assumption, we find that the Fox News viewership substantially increases racial animus and decreases perceived unacceptance. Next, using the structural parameter estimates, we find Fox News viewership increases most xenophobic behaviors, both in the short and long run[12]. In the short run, if everyone watched Fox News, a resulting increase of xenophobic behaviors between 39% and 54% would occur. In the long run, the increases would be between -2% and 57%.

Our work extends the small literature on the structural estimation of Bénabou and Tirole (2006)-type model (Butera et al. (2021), Chandrasekhar et al. (2018), Dubé et al. (2017)). Compared to Butera et al. (2021), we develop an empirical strategy to estimate any (pooling or separating) equilibrium of Bénabou and Tirole (2006)-type model, in which an action may not have a one-to-one mapping with (unobservable) types, and we allow for multidimensional types, including one that captures heterogeneous image concerns. Compared to Chandrasekhar et al. (2018), we allow for continuous multidimensional types, which are only noisily measured in data, so that they add challenges in identification. Compared to Dubé et al. (2017), we propose an empirical strategy to achieve point identification despite potential multiple equilibria and to allow a flexible functional form of the marginal distribution of types. Aside from these papers, DellaVigna et al. (2016) and Karing (2019) estimate a value of social signaling without estimating the underlying structure. Among non-structural works, Jia and Persson (2021) and Besley et al. (2019) find empirical evidence consistent with the prediction

[10]Ideally, we would have liked to use an instrumental variable strategy to consider endogeneity in Fox News viewership, but we could not find a strong instrumental variable. Following Martin and Yurukoglu (2017a), we tried an instrumental variable (IV) research design using the cable TV channel lineup position as an IV. However, we had a weak IV problem, so we decided not to use an IV design although it is a much better design to prove causality. We conjecture the reason why we had a weak IV problem in contrast to Martin and Yurukoglu (2017a) is because our Fox News channel viewership is self-reported, so it may include measurement errors. Martin and Yurukoglu (2017a) used data with plausibly little measurement error because their TV usage history was recorded using a device attached to TVs. Also, there has been a rise in streaming TV services which do not have the long channel lineups. This could have weakened the relevance of the IV.

[11]To examine the degree of maximal selection bias, we use the Altonji et al. (2005) - Oster (2019) estimator to compute the bound on OLS estimand when the selection from unobservable is equal to the selection from observables ($\delta = 1$ in Oster (2019)). We set the $Rmax = 1.3 \times R^2$ following the recommendation in Oster (2019). We find the OLS coefficient of Fox News viwership for racial animus can be biased downward by 12% and for perceived unacceptance, it can be biased upward by 22% under an equal selection assumption. These bounds are conservative if our controls explain most variation in Fox News viewership.

[12]Fox News marginally decreases one xenophobic behavior (during the dictator game) in the long run due to an increase in reputational gain.

of Bénabou and Tirole (2006) model in the context of name choice of minorities in China and tax evasion in the UK.

Our identification strategy in the presence of multiple equilibria extends the discussion in de Paula (2013), Bisin et al. (2011), Moro (2003), Bisin et al. (2004), and Fu (2014). de Paula (2013) provided a literature review on the identification and estimation of models with multiple equilibria. Bisin et al. (2011) proposed a two-step maximum likelihood estimator for a general class of models with multiple equilibria. Our paper shares a similar spirit with Bisin et al. (2011), and we estimate our model in several steps – including Indirect Inference in the very last step – due to the challenge imposed by multiple equilibria. The following papers – Moro (2003), Bisin et al. (2004), and Fu (2014) – estimated a model with multiple equilibria. Moro (2003) estimated a model of wage discrimination in the labor market and showed point identification can be achieved under parametric assumptions. Bisin et al. (2004) estimated a model of interreligious marriage and introduced a heuristic equilibrium selection rule which can be used in the estimation. Fu (2014) estimated an equilibrium model of college tuition, admission policy, and students' application and enrollment behavior and used a two-step estimation strategy similar to Moro (2003). Our paper demonstrates an example of how to achieve point identification in a model of xenophobia.

Finally, our structural work complements several reduced-form studies and applied theory on xenophobia. Lu and Sheng (2020) documented the rise of xenophobia against Asians during the pandemic. We complement this finding by making a long-run prediction of the pandemic on xenophobia, which is infeasible without theory due to the short timespan of data at the time of writing this paper. We find the pandemic's effect on anti-Chinese xenophobia can be different in the long run because of changing reputational gains associated with xenophobic (in)actions. Bursztyn et al. (2020) studied the effect of the rise of Donald Trump on the expression of xenophobic views and emphasized the role of perceived unacceptance on xenophobic behaviors. We strengthen this finding by providing a structural model to quantify the relative importance of racial animus and perceived unacceptance and to make a long-run prediction under various counterfactuals. Glaeser (2005) provided a theoretical framework about how xenophobia can get spread with false news. Our analysis on the role of the Fox News viewership on Sinophobia extends this work of Glaeser (2005) by showing how to empirically study the role of false news on xenophobia. Finally, our work extends several recent empirical studies on the effect of Fox News viewership – Martin and Yurukoglu (2017b), Ananyev et al. (2021), Ash et al. (2020), Bursztyn et al. (2020), Simonov et al. (2020) – by finding its effect on xenophobia against a minority, which has not been studied yet.

The remaining paper is structured as follows. Section 2 presents a signaling game of xenophobic behavior. Section 3 explains an identification and estimation strategy. Section 4 explains our survey design. Section 5 presents descriptive statistics and reduced-form evidence.

Section 6 shows structural estimation results and the validation using the information RCT. Section 7 gives various counterfactual predictions. Section 8 concludes the paper.

2 A signaling game of xenophobic behavior

We adopt Bénabou and Tirole (2006)'s signaling game model and explain xenophobic behavior using two motivations : intrinsic motivation to express anti-Chinese animus and reputational motivation to maintain good social image[13].

2.1 An agent's problem

There is a continuum of agents whose types (ν, μ) are distributed according to a continuous joint distribution $F(\nu, \mu)$. ν is a racial animus, which increases the intrinsic gain from a xenophobic action. μ is the perceived social (un)acceptance of racial animus. Each agent takes the social expectation on racial animus conditional on xenophobic action a, $E[\nu|a=1]$, $E[\nu|a=0]$, as given.

The following equation describes an agent's problem.

$$\max_{a\in\{0,1\}} \quad (\nu - (\kappa\mu + c)E[\nu|a=1]) + \epsilon_1)a + (-(\kappa\mu + c)E[\nu|a=0] + \epsilon_0)(1-a) \tag{1}$$

$$(\nu, \mu) \sim F(\nu, \mu), \quad \epsilon_1, \epsilon_0 \overset{iid}{\sim} \text{Gumbel}(0, \beta), \quad \kappa > 0$$

Each agent chooses between $a = 1$, a xenophobic action, and $a = 0$, a xenophobic inaction. $\mu E[\nu|a=1]$ is the perceived stigma from a xenophobic action, and $\mu E[\nu|a=0]$ is the perceived honor from not making a xenophobic action. Both stigma and honor are determined at social equilibrium, reflecting who of which racial animus type ν commits a xenophobic action. κ is a parameter for relative reputational concern. c is a location parameter for μ. ϵ_1, ϵ_0 is an idiosyncratic preference shock for committing a xenophobic action and inaction, which follow a Gumbel distribution with a scale parameter β.

Our model reflects normalization choices. First, the location and scale of ν and the scale of μ does not affect the solution. However, the location of μ changes the counterfactual prediction[14]. Therefore, we add a location parameter for μ. The scale of the agent's problem is normalized by setting the coefficient in front of ν to be 1, and the κ captures the relative scale

[13] Bénabou and Tirole (2006) included extrinsic motivation in the model, but we omit this because, for most xenophobic behaviors we consider, extrinsic motivation, like material payoff, is irrelevant.

[14] We thank Chris Taber for this comment.

between ν and μ. The location and scale of ν, μ distribution, and $F(\nu, \mu)$, are later anchorized using one proxy variable each respectively (Assumption 2). Note that after translating the μ distribution by $\frac{c}{\kappa}$ which can take any sign, the support of μ can include negative values - that is, we do not rule out the situation where racial animus is perceived as praiseworthy to some agents.

$$F(\nu,\mu) = C^{Joe}(F(\nu), F(\mu); \theta) \tag{2}$$

To model a joint density of the type (ν, μ), we model each marginal distribution and the dependence structure separately. Each marginal distribution can be fully nonparametric. The dependence structure is modeled with a Joe copula, which is an Archimedean copula with a single parameter θ[15].

Next, we define an equilibrium in this signaling game.

Definition 1 (Equilibrium)**.** *An equilibrium consists of an action $a^*(\nu,\mu,\epsilon_1,\epsilon_0)$ and the reputational gain $E^*[\nu|a=1] = E^*[\nu|a=0]$ such that*

1. For every individual, $a^*(\nu,\mu,\epsilon_1,\epsilon_0)$ is optimal given the reputational gain $E^*[\nu|a=1] - E^*[\nu|a=0]$. That is, $a^*(\nu,\mu,\epsilon_1,\epsilon_0)$ is a solution to the individual's problem defined in an equation 1.

2. The reputational gain $E^*[\nu|a=1] - E^*[\nu|a=0]$ is consistent with an individuals' behavior. That is,

$$E^*[\nu|a=1] - E^*[\nu|a=0] = \int_{(\nu,\mu,\epsilon_1,\epsilon_0)} \nu dF(\nu,\mu,\epsilon_1,\epsilon_0|a^*=1) - \int_{(\nu,\mu,\epsilon_1,\epsilon_0)} \nu dF(\nu,\mu,\epsilon_1,\epsilon_0|a^*=0) \tag{4}$$

As is well known, a signaling game may have multiple equilibria, and the conditions to have a unique equilibrium in a general signaling model are unknown.[16] We do not constrain our model to have a unique equilibrium but we prove that this does not cause an issue in identification (Proposition 1): the structural parameters can be point identified under the assumption that we know which part of the data is generated from a single equilibrium[17]. Assumption 1 states that all the data is generated from a single equilibrium. This assumption can be restrictive if the reputational gains are different due to geographic segregation. We examine whether reputational gains are substantially different across different US regions in

[15]The copula choice was made after observing patterns in data. The Joe copula fits the empirical joint density well. The Joe copula formula is as follows :

$$C^{Joe}(u,v;\theta) = 1 - [(1-u)^\theta + (1-v)^\theta - (1-u)^\theta(1-v)^\theta]^{1/\theta}, \quad \theta \in [1,\infty). \tag{3}$$

[16]Bénabou and Tirole (2006) provides conditions for a unique equilibrium in related but different models.

[17]For example, one can assume that the observations from a same group unit, such as a village or a school, are generated from the same equilibrium.

our data and find they are not significantly different (Figure B.1 in Online Appendix). Therefore, we assume that the entire data was generated from a single equilibrium.

Assumption 1. *The data is generated from a single equilibrium.*

We numerically examine whether there are multiple equilibria. We find there are multiple equilibria under the structural parameter estimates (Figure 10). Our estimation strategy does not require an equilibrium selection rule but the counterfactual analysis does. In our counterfactual analysis, we adopt an equilibrium selection rule to choose the new equilibrium with a reputational gain closest to the baseline level. This selection rule is reasonable if an abrupt jump to a significantly different equilibrium is unlikely.

2.2 Auxiliary model for counterfactual analysis

We build an auxiliary model to explain how a factor D may shift the joint density of racial animus and perceived unacceptance, $F(\nu,\mu)$. Next, we make counterfactual predictions on how D changes an equilibrium on xenophobia using the structural model in equation 1.

For tractability, we assume the dependence between ν and μ stays invariant under counterfactuals and a factor D shifts the marginal distribution of the key latent variables $\{\nu,\mu\}$[18]. We use a set of quantile regressions in equations 5 and 6 where the dependent variables are the proxies of latent variables $\hat{\nu},\hat{\mu}$, and the regressors are the factor of interest, D, and other covariates X.[19] Later, we use the information RCT treatment, the COVID related experience, and Fox News viewership as factors D shifting the distribution of $\{\nu,\mu\}$. The proxies of latent variables are constructed as the average of normalized proxies defined in equation 19, 20, $\frac{\sum_k \tilde{Z}_k^\nu}{N^\nu}, \frac{\sum_g \tilde{Z}_g^\mu}{N^\mu}$. To interpret $\{\alpha^\nu(\tau),\alpha^\mu(\tau)\}$, the effect of a factor D causal, we make either an independence assumption or conditional independence assumption - that is, the potential outcomes of (ν,μ) and the factor D are independent unconditionally or conditionally on covariates X[20]. Given the auxiliary model estimates and our structural parameter estimates $\{\kappa,c,\beta\}$, we can predict xenophobic behavior a under a counterfactual.

$$P\left[\hat{\nu} < D\alpha^\nu(\tau) + X\gamma^\nu(\tau)|D,X\right] = \tau \quad \text{a.s.} \tag{5}$$

[18]For example, Bayer et al. (2019) made a similar assumption for simplification

[19]To the best of our knowledge, we are not aware of a quantile regression estimator applicable to a multivariate joint density.

[20]For information RCT treatment, an unconditional independence assumption is reasonable because we randomized the treatment. For COVID-related experiences and Fox News viewership, we rely on a conditional independence assumption.

$$P\left[\hat{\mu} < D\alpha^{\mu}(\tau) + X\gamma^{\mu}(\tau)|D, X\right] = \tau \quad \text{a.s.} \tag{6}$$

We define the short-run counterfactual outcome as the outcome when we hold the reputational gain fixed at the previous level. The long-run counterfactual outcome is defined as the outcome when we update the reputational gain to a new level consistent with the individual's behavior. It is a merit of a structural model to be able to produce long-run predictions even though the data covers a short time span.

Note that the long-run counterfactual outcome takes into consideration the social multiplier effect. The shift in the distribution of (v, μ) will make the marginal types engage in or refrain from xenophobic behavior a. Next, the reputational gain $E[v|a=1] - E[v|a=0]$ will change reflecting the change in types who commit the xenophobic behavior. And the change in reputational gain will make the marginal types change their xenophobic behavior. These updates will continue until the reputational gain becomes consistent with the individual's behavior.

2.3 Measurement equations for proxies

We collect proxies for the type (v, μ) from our survey. To identify measurement errors, we collect multiple proxies (Cunha et al. (2010)), more than three each for (v, μ) - that is, $N_v \geq 3$ and $N_\mu \geq 3$. We assume the following measurement equations hold.

$$Z_k^v = \alpha_{k0}^v + \alpha_{k1}^v v + \epsilon_k^v, \quad k \in \{1, \cdots, N_v\}, \quad \epsilon_k^v \overset{i.i.d.}{\sim} N(0, \sigma^2_{\epsilon_k^v}) \tag{7}$$

$$Z_g^\mu = \alpha_{g0}^\mu + \alpha_{g1}^\mu \mu + \epsilon_g^\mu, \quad g \in \{1, \cdots, N_\mu\}, \quad \epsilon_g^\mu \overset{i.i.d.}{\sim} N(0, \sigma^2_{\epsilon_g^\mu}) \tag{8}$$

The above system of equations is unidentified unless we anchor proxy variables[21]. Therefore, we make the following anchorization assumption following Cunha et al. (2010). Under Assumption 2, the location and the dispersion of the joint density of (v, μ), $F(v, \mu)$, are anchored. Note that the agent's problem in equation 1 allows for a location parameter c which makes the model prediction invariant to the translation of $F(v, \mu)$ along the μ dimension.

Assumption 2 (Anchorization)**.** *For normalization, we assume* $\alpha_{10}^v = \alpha_{10}^\mu = 0$ *and* $\alpha_{11}^v = \alpha_{11}^\mu = 1$.

[21] The exception is α_{10}^μ. An alternative identification strategy is to not anchor α_{10}^μ but omit c in equation 1. However, then it is difficult to use the sequential estimation strategy we use, which is key to gain point identification in the presence of potential multiple equilibria. So we choose to anchor α_{10}^μ and allow for an additional location parameter c in equation 1.

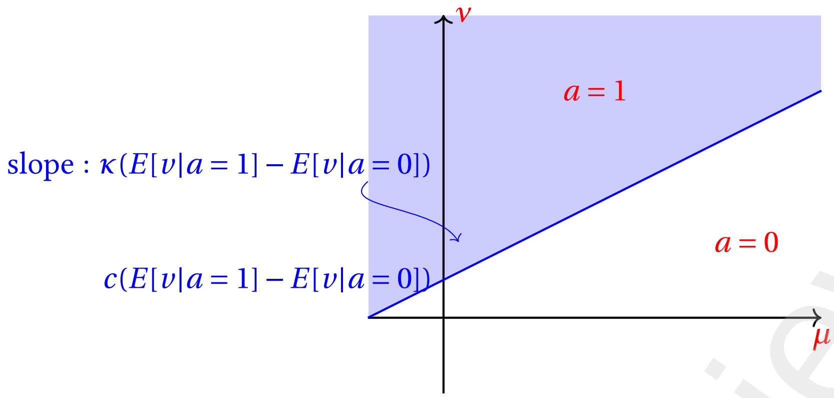


Figure 1: Graphical illustration of an equilibrium

We choose proxy variables $\{Z_1^\nu, Z_1^\mu\}$, that are most correlated with other proxy variables to anchor the location and the scale of (ν, μ). This is to reduce the variance of measurement equation parameter estimates, as the covariance between the anchor proxy variable and another proxy variable inversely affects the factor loading parameter through changing $Var(\nu)$ in equation 14. Therefore, large covariance between the anchor proxy variable and other proxy variables helps reduce the variance in the estimates. In Online Appendix Section F, we replicate our main results when we use different proxy variables to anchor the location and the scale of (ν, μ)[22].

3 Identification and Estimation

3.1 Identification

Despite multiple equilibria, we can achieve point identification by using proxies for the latent variables (ν, μ) and doing estimation in steps.

Proposition 1. *Structural parameters* (κ, c, β) *can be point identified from our data given the distribution* $F(\nu, \mu)$ *and the reputational gain* $E[\nu|a = 1] - E[\nu|a = 0]$.

Proof. In the Appendix. □

To explain the key idea in the proof, we first estimate the reputational gain $E[\nu|a = 1] - E[\nu|a = 0]$, joint density $F(\nu, \mu)$, and measurement equation parameters in equation 7, 8 independently before estimating structural parameters (κ, c, β). This is feasible because we have enough proxies for ν and μ. Next, in the Indirect Inference, we target moments which

[22]Structural parameter estimates change because of different normalization. We confirmed most model predictions remain qualitatively similar.

have one-to-one correspondence to the structural parameters (κ, c, β) jointly given the measurement equation parameters. They are the regression coefficients from regressing the xenophobic action $a = 1$ on the average normalized proxies of ν and μ and the average xenophobic action $\bar{a}$ obtained from the data. To visualize this, Figure 1 shows a graphical illustration of an equilibrium. The figure shows the projection of $F(\nu, \mu, \epsilon_1, \epsilon_0)$ onto the $(\nu,\ \mu)$ plane and the separating hyperplane to delineate an area corresponding to the xenophobic action $a = 1$ from an inaction $a = 0$. Note that the separating hyperplane has a one-to-one mapping to parameters (κ, c), holding the reputational gain $E[\nu|a=1] - E[\nu|a=0]$ fixed. Holding the joint density $F(\nu, \mu)$ and the reputational gain $E[\nu|a=1] - E[\nu|a=0]$ fixed, the moments (ξ_0, ξ_1, ξ_2) have one-to-one mapping with (κ, c). Next, given the every other estimate, $P(a=1)$ identifies β.

3.2 Estimation

We estimate our model in several steps. First, we estimate the measurement equation parameters, the joint density $\widehat{F(\nu, \mu)}$, and the reputational gain $E\widehat{[\nu|a=1]} - E\widehat{[\nu|a=0]}$. Next, we estimate the structural parameter (κ, c, β) using the Indirect Inference given the other estimates.

We explain each estimation step below.

1. **Estimating measurement equation parameters**
   The measurement equation parameters $\{\alpha^\nu_{k0}, \alpha^\nu_{k1}, \alpha^\mu_{g0}, \alpha^\mu_{g1}, \sigma^2_{\epsilon^\nu}, \sigma^2_{\epsilon^\mu}\}$ can be easily identified using the result in Cunha et al. (2010).

$$Var(\nu) = \frac{\sum_{(k,k')} \frac{Cov(Z^\nu_1, Z^\nu_k) Cov(Z^\nu_1, Z^\nu_{k'})}{Cov(Z^\nu_k, Z^\nu_{k'})}}{\sum_{(k,k')} 1}, \quad 1 < k, k' < N^\nu, k \neq k' \tag{9}$$

$$Var(\mu) = \frac{\sum_{(k,k')} \frac{Cov(Z^\mu_1, Z^\mu_k) Cov(Z^\mu_1, Z^\mu_{k'})}{Cov(Z^\mu_k, Z^\mu_{k'})}}{\sum_{(k,k')} 1}, \quad 1 < k, k' < N^\mu, k \neq k' \tag{10}$$

$$E[\nu] = E[Z^\nu_1] \tag{11}$$

$$E[\mu] = E[Z^\mu_1] \tag{12}$$

$$\alpha^\nu_{k1} = \frac{Cov(Z^\nu_1, Z^\nu_k)}{Var(\nu)} \tag{13}$$

$$\alpha^\mu_{k1} = \frac{Cov(Z^\mu_1, Z^\mu_k)}{Var(\mu)} \tag{14}$$

$$\alpha^\nu_{k0} = E[Z^\nu_k] - \alpha^1_k E[\nu] \tag{15}$$

$$\alpha^{\mu}_{k0} = E[Z^{\mu}_k] - \alpha^1_k E[\mu] \tag{16}$$
$$\sigma^2_{\epsilon^\nu} = Var(Z^\nu_k) - \alpha^2_{k1} Var(\nu) \tag{17}$$
$$\sigma^2_{\epsilon^\mu} = Var(Z^\mu_k) - \alpha^2_{k1} Var(\mu) \tag{18}$$

$Var(\nu), Var(\mu)$ are overidentified in the model because $Var(\nu) = \frac{Cov(Z^\nu_1, Z^\nu_k)Cov(Z^\nu_1, Z^\nu_{k'})}{Cov(Z^\nu_k, Z^\nu_{k'})}$ and $Var(\mu) = \frac{Cov(Z^\mu_1, Z^\mu_k)Cov(Z^\mu_1, Z^\mu_{k'})}{Cov(Z^\mu_k, Z^\mu_{k'})}$ for $\forall k, k'$ such that $k, k' \neq 1, k \neq k'$. We take an average of results obtained from all possible pairs (k, k') to estimate $Var(\nu)$ and $Var(\mu)$.

2. **Estimating the marginal densities of ν and μ**

   Using the estimates of the measurement equation parameters, we construct normalized proxies, which have error-in-variable structures.

$$\tilde{Z}^\nu_k = \frac{Z^\nu_k - \alpha^\nu_{k0}}{\alpha^\nu_{k1}} = \nu + \tilde{\epsilon}^\nu_k, \quad k \in \{1, \cdots, N_\nu\}, \quad \tilde{\epsilon}^\nu_k \overset{i.i.d.}{\sim} N\left(0, \left(\frac{\sigma_{\epsilon^\nu}}{\alpha^\nu_{k1}}\right)^2\right) \tag{19}$$
$$\tilde{Z}^\mu_k = \frac{Z^\mu_k - \alpha^\mu_{k0}}{\alpha^\mu_{k1}} = \mu + \tilde{\epsilon}^\mu_k, \quad k \in \{1, \cdots, N_\mu\}, \quad \tilde{\epsilon}^\mu_k \overset{i.i.d.}{\sim} N\left(0, \left(\frac{\sigma_{\epsilon^\mu}}{\alpha^\mu_{k1}}\right)^2\right) \tag{20}$$
$$\tag{21}$$

   Next, we apply a Li and Vuong (1998) deconvolution kernel estimator to the normalized proxy variables to estimate the nonparametric density of ν and μ. We followed Delaigle and Gijbels (2004) and Kato et al. (2021) to choose the bandwidth for Li and Vuong (1998) estimator.

3. **Estimating the Joe copula parameter θ**

   We estimate the Joe copula parameter θ to match the correlation between average z-scores of proxies of racial animus and perceived unacceptance with a simulated sample given the estimates from 1 and 2 above. The simulation sample size is five times larger than our data size.

4. **Estimating the reputational gain $\widehat{E[\nu|a=1]} - \widehat{E[\nu|a=0]}$**

   We estimate the reputational gain using the normalized proxy variables of racial animus.

$$\widehat{E[\nu|a=1]} - \widehat{E[\nu|a=0]} = \frac{\sum_k \sum_i \tilde{Z}^\nu_{ik} \mathbb{1}(a_i = 1)}{\sum_k \sum_i \mathbb{1}(a_i = 1)} - \frac{\sum_k \sum_i \tilde{Z}^\nu_{ik} \mathbb{1}(a_i = 0)}{\sum_k \sum_i \mathbb{1}(a_i = 0)} \tag{22}$$

5. **Estimating the structural parameters (κ, c, β) through Indirect Inference**

   We estimate the structural parameters (κ, c, β) by Indirect Inference (Gourieroux et al. (1993)). We let the structural parameters to vary by xenophobic actions. We have three xenophobic action measures, so we estimate nine structural parameters in total. For each xenophobic action, we match five moments : regression coefficients $\{\xi_0, \xi_1, \xi_2\}$ regressing the xenophobic action on average z-score of racial animus and perceived unacceptance, average xenophobic action $P(a=1)$, and the model predicted reputational gain $E[v|a=1]-E[v|a=0]$.

$$P(a=1)=\xi_0+\xi_1\left(\frac{\sum_k \tilde{Z}_k^{v}}{N^{v}}\right)+\xi_2\left(\frac{\sum_g \tilde{Z}_g^{\mu}}{N^{\mu}}\right) \tag{23}$$

We use a diagonal weighting matrix with a diagonal that includes the inverse of the variance of each moment (Altonji and Segal (1996)). We estimate the variance of each moment using 100 bootstrap samples.

The objective function of Indirect Inference is non-differentiable due to discreteness in a choice variable. To smooth the objective function, we use a simulation sample five times larger than our data size, and we do an extensive grid search and use the Nelder-Mead algorithm (Nelder and Mead (1965)) for estimation.[23]

To account for the cumulation of sampling errors, the standard errors are computed by repeating the entire estimation procedure 100 times using bootstrap sample with replacement.

4 Survey Design

This section explains our survey design. We conducted a 15-minute online survey through a survey firm Respondi. The firm Respondi sent invitation emails to their panel members. The survey has started on March 24, 2021 and finished on May 24th, 2021. After dropping low-quality responses, our sample includes 2,363 non-Asian individuals living in the US, who are aged between 18 and 70 years old. We stratified our sample in terms of gender, race, education, age, marital status, and income[24]. We paid $2.25 for each complete 15 minute survey and we paid extra rewards based on their answers. Respondi survey firm has set different compensation amounts to the survey participants based on their demographics.

Figure 2 shows our survey flow. Appendix D shows a few selected survey questions and

[23]We have considered using a generalized Indirect Inference (Bruins et al. (2018)) but decided not to use it because it requires substantial amount of smoothing to remove kinks in our data but then it brings too much bias in the estimates.

[24]We exclude a non-Chinese Asian sample from the analysis. Non-Chinese Asians comprise only 3% of the US population, and therefore, whether including this population in the analysis will not change our results much. Understanding non-Chinese Asians' Sinophobia may be interesting, but this will require oversampling non-Chinese Asians, which was not feasible in our project due to cost concerns. Another reason why they are excluded is that non-Chinese Asians may have very different motivations for their bias against Chinese people, so including them would make our sample more heterogeneous. Many non-Chinese (east) Asians are difficult to distinguish from Chinese individuals physically, so they also became victims of hate crimes during the pandemic (Tessler et al. (2020)).

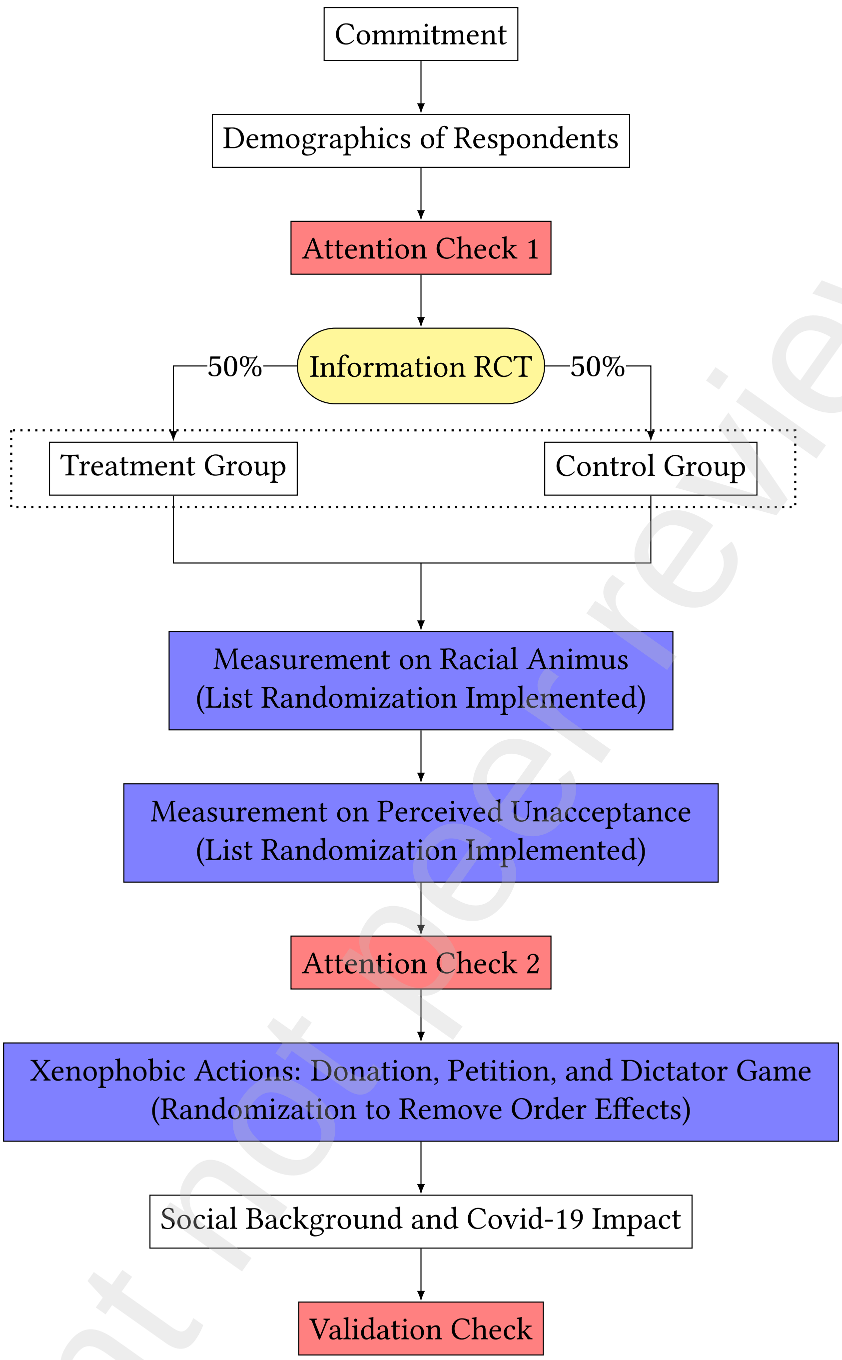


Figure 2: Survey Flow

provides a link to take our survey online. To view the complete survey questionnaire, see Online Appendix G.

4.1 Ensuring high-quality survey responses

We carefully designed our survey to ensure high-quality responses.

First, we worded our survey invitation and consent form carefully to avoid selective participation by anti-Chinese racial animus or perceived unacceptance of racial animus. The invitation email did not mention keywords, such as 'anti-Chinese' or 'xenophobia'. Instead, the email invitation started by saying, "New Survey Available!" in the headline, and the email body said "(NAME), you've been pre-qualified to participate in a survey. This survey is only available for a short time, so please respond ASAP!" In the consent form, we described the purpose of our survey vaguely to hide the specific survey topic without deceiving respondents. We said, "The purpose of this survey is to understand the social preferences of people living in the US". We hid our names in the consent form and introduced ourselves as a "non-partisan group of researchers" from University, as our names signal Asian ethnicity and knowing that the research team members are Asians may contaminate the responses.

Second, we asked respondents explicitly at the beginning of the survey to commit to reading the survey carefully and providing honest responses to the best of their ability. Specifically, we said, "You have been selected to represent a portion of the US population. The results from the survey can influence political decisions and thus affect the lives of many people. In order for the information from this research to be the most helpful, it is important that you try to be as accurate, complete, and honest as possible with your answers. To do this, it is important to think carefully about each question, search your memory, and take time in answering. Are you willing to do this?". Cibelli (2017) showed that such an explicit commitment improves the quality of the online survey. We exclude those who refuse to commit to these standards.

Third, we included several quality-check questions to screen out participants paying little attention to our survey and to make participants more attentive throughout the survey. This was recommended by Berinsky et al. (2014), who proved multiple screener questions are effective at improving the quality of online surveys. We inserted two screener questions before important survey blocks which measure key variables (Figure 2). You can find the two screener questions in the Appendix D.2. The first screener question pretended to be a question about current feelings, but we asked respondents to check only "None of the above" to prove that they are attentive. We inserted the first screener question just before our information RCT treatment which was followed by questions about racial animus and perceived unacceptance. This was to make participants more attentive during the RCT treatment. The control group did not watch the information RCT treatment video. Instead, they started answering about their racial animus and perceived unacceptance of racial animus right after the first attention check question. The second screener question was masked as a question about an electronic device used for the survey participation, but we asked respondents to check "Other." We inserted this question before measuring xenophobic behaviors. Table 1 shows the pass rates

Table 1: Dropping low-quality responses

	Try	Pass	Pass rate (%)
Attention Check 1	10641	5187	48.75
Attention Check 2	5187	3372	65.01
Surveyor Demand Check	2723	2363	86.78
Final Sample Size		2363	

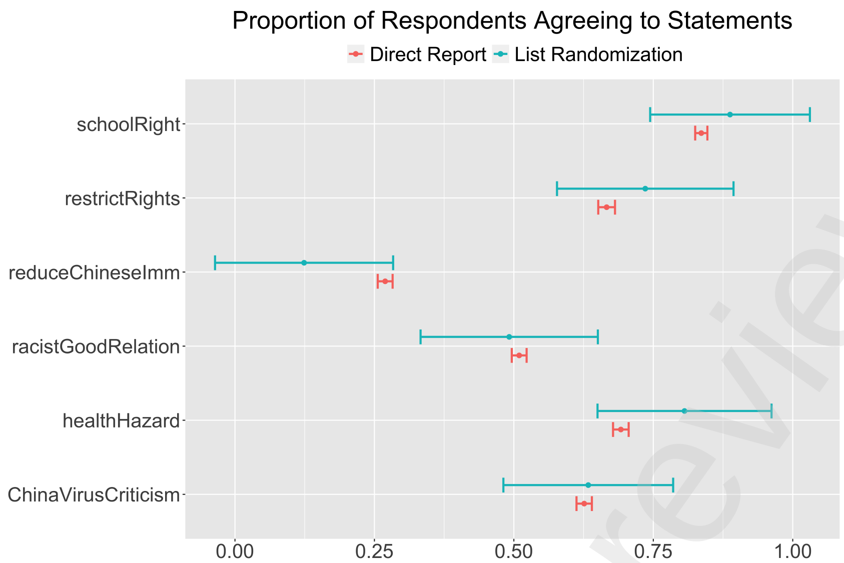
regarding our attention-check questions. Roughly, 40% to 50% of people failed to pass the attention check questions. The pass rate is similar to what people have found elsewhere in the literature (Berinsky et al. (2014)). In Online Appendix D, we show descriptive statistics about the screened sample. The people who failed to pass attention-check questions spent less time on responses and showed higher racial animus and lower perceived unacceptance.

Fourth, we included a question at the end of the survey asking whether the survey looked biased in favor of or against Chinese immigrants to detect any surveyor demand effect. We dropped a small number of respondents (13%, Table 1) who answered that the survey looked biased in either direction because their responses may not be honest. For robustness, we repeat our analysis by including the sample who reported the bias in our survey and we show the results in Online Appendix Section E[25].

Fifth, we included a battery of List randomization questions to assess social desirability bias. List randomization assigns respondents into either control or treatment groups. The control group was asked to report how many statements out of N neutral statements they agree with, and the treatment group answered a similar question but out of the same N neutral statements plus one extra sensitive statement. The difference between the average response of the control group and the treatment group reveals the fraction of people who agree to the sensitive statement plausibly without social desirability bias. This is because respondents do not have to specify which statement, including a sensitive one, they agree to. If the share of people who agree to the sensitive statement recovered from List randomization is statistically different from the share of people who agree to the sensitive statement in a direct question, it means there is a bias in the direct question, most likely due to social desirability. Each treatment group received one extra sensitive statement about either anti-Chinese animus or perceived unacceptance of racial animus. We carefully chose the neutral questions to avoid the large variance and potential bias in the List randomization responses, which are discussed as common weakness of the List randomization method (Glynn (2013), Hubbard et al. (1989)). Specifically, we investigated the 2018 ACS data to construct the neutral statements which give the smallest variance in responses and a good mix of prevalent and rare behaviors to prevent the floor or ceiling bias. The chosen four neutral statements are "I am a veteran," "I am living

[25]We confirmed most results remain qualitatively similar.

Figure 3: Test of Social Desirability Bias using List Randomization



Note : This figure shows the social desirability test for statements about racial animus ν and perceived unacceptance μ. We used statements that do not show evidence of social desirability bias.

with at least one sibling in this household," "I have a smartphone," "I have a health insurance coverage (of any kind, either public or private)." [26]

We used survey instruments for racial animus ν or perceived unacceptance μ which do not show the evidence of social desirability bias from the List randomization. Figure 3 compares the shares of people who agreed to a statement about either racial animus ν or perceived unacceptance μ from a direct question with the ones from a List randomization question. The figure shows a 95% confidence interval around the point estimates[27]. If the share from a List randomization question is not statistically different from the share from a direct question, there is no evidence of social desirability bias. We found some evidence of social desirability bias from statements included in our survey but we excluded them from our analysis so as not to contaminate the results with social desirability bias as much as possible. For the List Randomization test results for the full statements included in the survey, see Figure A.1 in the Online Appendix.

Sixth, we randomized the order of choice options in xenophobic behavior measures and the order of the identity of the sequential dictator game partners to remove any order effect. The earlier presented choice option might be implicitly understood as the desirable choice, or some respondents might have a tendency to check options that are presented either earlier or later. By randomizing the choice options, we removed such an order effect on average. Simi-

[26] Our neutral statements are similar to the ones used in Karlan and Zinman (2012).

[27] The confidence intervals from List randomization questions are much wider than the ones from direct questions. However, this is not an error. The high variance is common in List randomization estimates as well known in the literature (Hubbard et al. (1989)).

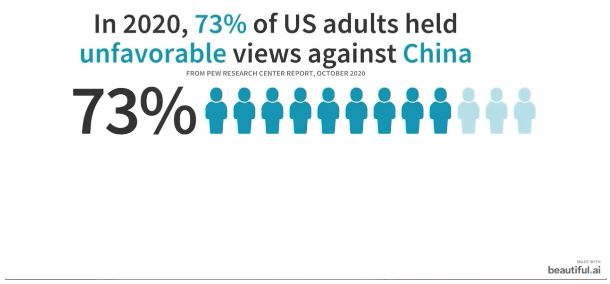


Figure 4: Screenshot of our information RCT video

larly, when we repeated the dictator game sequentially to measure altruism toward partners of different ethnicity, we randomized the order of the partners to mitigate any order effect.

4.2 Information Randomized Controlled Trial

We showed a one-minute video about how the pandemic is changing the perceptions of China and Chinese immigrants to a randomly chosen half of the participants (Figure 4). You can find the video we used from the YouTube link in the footnote below[28]. We made the video to include voice narration and animation to make it more interesting. We also incentivized viewers to pay more attention to the video. We told respondents before the treatment they would be given a lottery to win a small reward, worth the same as the base participation payment if they answer correctly about the video content later. Afterward, we asked whether they had any technical issues in playing the video on their device.

We distinguish the group randomized into treatment from the group who got effectively treated. We consider a participant was 'effectively treated' if they answered a post-treatment question about the video content correctly and if they reported no technical issue in playing the video afterward. Later, we present both intention-to-treat (ITT) estimates and local average treatment effect (LATE) estimates. To compute the local average treatment effect, we instrument the effective treatment using randomization into a treatment group. The complier rate was high, 87% (Table 7 footnote).

We found that the information treatment did not change social desirability bias in responses to questions about racial animus and perceived unacceptance of racial animus. This is shown in Figure C.1 in Online Appendix Section C. Figure C.1 compares the List randomization reports with direct reports by the treatment status. For both treated and control groups, the means from the List randomization were not statistically different from the means from

[28] https://www.youtube.com/watch?v=8sjOWt6PWdA

those of the direct report. Therefore, differences in the racial animus or perceived acceptance proxies by treatment status reflect the change in the latent variables of racial animus or perceived unacceptance, and these are not the artifact of different measurement errors by treatment status.

4.3 Measurement of Anti-Chinese Racial Animus and Perceived Unacceptance of Racial Animus

This section explains our survey instruments to measure anti-Chinese racial animus and perceived unacceptance of racial animus. Table 2 lists our survey instruments.

To measure anti-Chinese racial animus, we used a subset of questions developed by Social Psychologists (Stephan et al. (1999))[29]. We did not use their entire survey to limit the length of ours. The questions consisted of two types of questions. The first type of question asked how much respondents agree with each statement about Chinese immigrants in the US, which can reveal racial animus against Chinese immigrants. The second type of question inquired about the feelings towards Chinese immigrants. These questions are jointly used to identify a single latent variable, called 'anti-Chinese racial animus' v in the model.

Unlike the measures for anti-Chinese racial animus, we could not find similar survey instruments for the perceived unacceptance of racial animus against Chinese or Asian immigrants. Therefore, we developed our own survey instruments. The statements described how the typical American citizens would react to or judge a Sinophobic behavior.

We show that these survey instruments have high internal consistency in our Appendix (Table B.1 and B.2) and that they are related to the xenophobic behavior measures consistent with the model prediction (Table 5).

4.4 Measurement of Xenophobic Behavior

We collected a wide range of hypothetical and incentivized xenophobic behavior measures for a complete picture, including whether to donate to a Sinophobic institution, whether to sign a Sinophobic petition, and dictator game outcomes to measure altruism toward Chinese immigrants relative to White Americans[30]. The donation and petition questions were hypothetical choice questions. We hoped to design these questions to measure real donation and

[29] We took a subset of questions developed by Walter G. Stephan. http://psych.nmsu.edu/faculty/walter/asian_questionaire.pdf

[30] We also collected Tweets from a survey sample during the pandemic but do not use them for analysis because of severe selection in Twitter data.

Table 2: Survey instruments for anti-Chinese racial animus and perceived unacceptance of racial animus

	Anti-Chinese Racial Animus
Question	Please indicate your agreement with each of the following statements concerning immigration from China. (Slider scale from 0(strongly disagree) to 100(strongly agree))
Statement	• The children of Chinese immigrants should have the same right to attend public schools in the U.S. as Americans do. • Chinese immigrants do **not** pose any health hazards to U.S. citizens.
Question	For each of the items listed below indicate what your attitudes are toward Chinese immigrants. My attitude toward Chinese immigrants is : (Slider scale from 0(strongly disagree) to 100(strongly agree))
Statement	• Warmth • Hatred • Acceptance • Dislike
	Perceived Unacceptance of Racial Animus
Question	Please indicate your agreement with each of the following statements concerning the attitudes of **typical American citizens (below referred to as "people").** (Slider scale from 0(strongly disagree) to 100(strongly agree))
Statement	• Even though someone publicly says he/she dislikes Chinese immigrants, the person can still maintain good social relationships with most people. • People will criticize if someone calls the novel coronavirus "China virus." • It is **not** shameful to publicly support to reduce the number of Chinese immigrants because they threaten our prosperity. • It is **not** socially acceptable to make a public statement that the US government should restrict the rights of Chinese immigrants.

real petition signatures following Elías et al. (2019) and Grigorieff et al. (2018), but the Homewood IRB did not allow such research designs[31]. One drawback of using hypothetical choice questions is that respondents may not consider their choices seriously. To complement these questions, we made our participants play a dictator game, which was incentivized with real money at stake.

Below, we briefly describe each of these behavioral measures. You can find the questions we used in Appendix D.4. First, in the donation question, we gave a short description of two

[31] The Homewood IRB viewed including the real donation question and the real petition question as a political activity, which is not allowed for research.

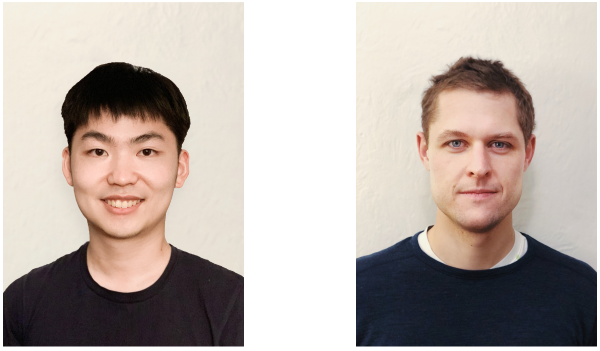


Figure 5: Pictures of the receiver players in a dictator game.
Left player's name: Haozheng, Right player's name: Peter

different organizations, with opposing stances on Chinese immigrants. One organization defined Chinese students and scholars as potential spies and urged restricting the entry of Chinese students and scholars into the US. The other organization made the opposite claims. We asked if respondents would like to donate $1 hypothetically to either organization. If respondents chose the organization with a hostile attitude toward Chinese students and scholars, we coded it as xenophobic behavior.

Second, we gave two short petitions for participants to review. One petition called for national efforts to protect US security and wealth from the threats posed by Chinese immigrants. The other petition urged defending the Chinese immigrants' safety and rights. If respondents opted to sign the former petition, we coded it as xenophobic behavior.

Third, our dictator game was incentivized with real money at stake and did not include any deception. We recruited one Chinese immigrant and one White American to become a receiver player and paid them according to the dictator game outcomes. Every survey participant played the dictator game twice with both receiver players in a random order. To save on survey costs, we told them 10% of our sample will be randomly selected to be paid according to their responses. We emphasized that their choices in the game will not affect the probability to be selected for payment. In the dictator game, we showed the receiver players' headshot photos and their first names, which signal their ethnicity, and asked them to choose how much to share with the receiver players if they are given $1 to share. $1 is small but is close to the base participation reward. Therefore, by making the most selfish decisions, participants can earn 200% of the base participation reward if they are selected to be paid[32]. If participants shared more money with a White American than with a Chinese immigrant, we coded it as xenophobic behavior[33].

[32] This is because they play the dictator game twice with a different receiver player.

[33] In our reduced-form analysis, we present the results using the share difference between a White American and a Chinese immigrant. We do not include the share difference in our structural analysis because our model explains a binary discrete choice.

5 Descriptive Statistics and Reduced-Form Evidence

This section presents descriptive statistics about our survey sample and the reduced-form evidence which supports our model.

5.1 Descriptive Statistics

Our sample matches the non-Asian US population reasonably well, although not perfectly due to the limitations of an online panel survey. We re-weight our sample to match the non-Asian US population in our reduced-form analysis using the weight provided by the survey firm. Table 3 compares our sample with the characteristics of the representative non-Asian US population. So far, our sample matches this population well in terms of gender, race, and marital status. We have fewer young people aged between 18 and 29, more older people aged between 60 and 70, more lower-income people, fewer higher-income people, fewer people from the West, and more people from the Northeast and Midwest.

We asked questions regarding COVID-related experiences in our survey. Later, we will show how COVID-related experiences change racial animus and perceived unacceptance and will make counter factual predictions about how xenophobia could have been different if a COVID outbreak had never occurred. Table 4 shows the summary statistics of these questions. A substantial number of respondents either got infected with COVID or knows someone close to them who did; specifically, about 8% of our sample got infected with COVID and 26% have a family member who did. Among those who had a job before the pandemic, 12% lost their job and 46% had to continue working face-to-face.

Table 4: COVID related experience statistics

Statistic	N	Mean
COVID self	2,354	0.079
COVID family	2,349	0.262
COVID relative	2,349	0.289
COVID friend	2,349	0.390
Job loss	1,318	0.118
Work face-to-face	1,318	0.458
Telework at home	1,318	0.424

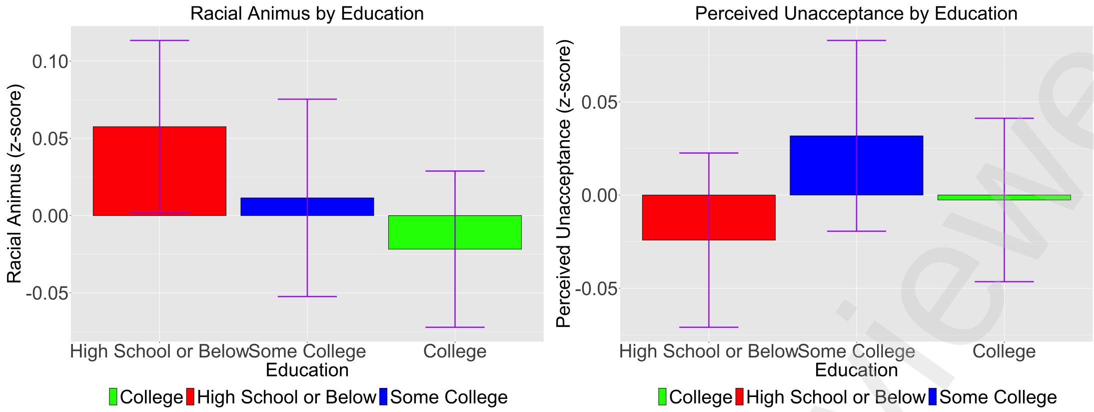
Table 3: Sample Balance

	Main Survey	US Population
Male	0.45	0.50
18-29 years old	0.19	0.24
30-59 years old	0.58	0.57
60-70 years old	0.24	0.19
High School or Below	0.37	0.45
Some College	0.28	0.25
College	0.36	0.30
White	0.80	0.78
Black/African American	0.11	0.14
Others	0.09	0.07
Married	0.50	0.49
$0˜$38754	0.32	0.25
$38755˜$73978	0.31	0.25
$73979˜$129066	0.24	0.25
$129067+	0.14	0.25
Northeast	0.22	0.17
Midwest	0.24	0.21
South	0.38	0.39
West	0.15	0.22
Sample Size	2363	

Note: Asian Americans excluded; Household income data come from ASEC CPS 2019 (Flood et al. (2021)); Other U.S. population data come from ACS 2019 (Ruggles et al. (2021)).

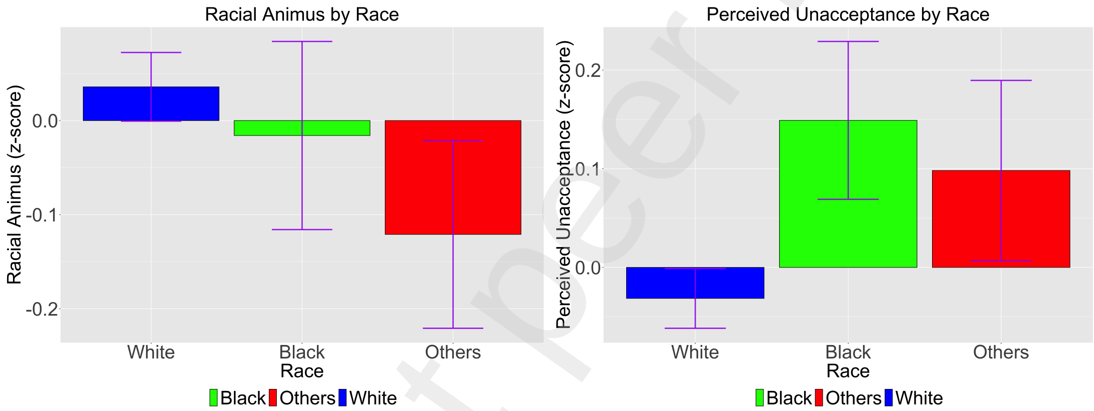
We compare racial animus and perceived unacceptance by education groups and racial groups. Figure 6 shows racial animus and perceived unacceptance by education groups. Contrary to our prior belief, racial animus differs by education group, but we do not find much difference in perceived unacceptance by education group. Before seeing the results, we conjectured that there may be more differences in perceived unacceptance by education groups than in racial animus. Next, we compare different racial groups. Figure 7 shows that Whites have notably higher racial animus and lower perceived unacceptance compared to other groups. Black respondents' racial animus is not much lower than that of Whites, but they show the highest perceived unacceptance of racial animus.

Figure 6: The difference in racial animus and perceived unacceptance by education groups



Note: Others mean non-White, non-Black, and non-Asian—for example, Hispanic.

Figure 7: The difference in racial animus and perceived unacceptance by racial groups



Note: Others mean non-White, non-Black, and non-Asian—for example, Hispanic.

5.2 Reduced-Form Evidence for Theory

Table 5: Reduced-Form Evidence for Theory

	Dependent variable:			
	Xenophobic Donation	Xenophobic Petition	(DG) 1(White>Chinese)	(DG) (White-Chinese)
Racial Animus (z-score)	0.122***	0.125***	0.094***	2.435***
	(0.011)	(0.008)	(0.008)	(0.296)
Perceived Unacceptance of Racial Animus (z-score)	−0.166***	−0.056***	−0.030***	−0.546
	(0.014)	(0.010)	(0.010)	(0.355)
Weighted Average of Dependent Variable	0.232	0.098	0.097	-0.138
Observations	2,148	2,148	2,148	2,148
R^2	0.184	0.168	0.087	0.046

Note: DG stands for dictator game. The dependent variable in the third column is whether a respondent shared more with a White American than with a Chinese immigrant. The dependent variable in the fourth column is the difference between the share with a White American and the share with a Chinese immigrant.
***p<0.01

The data confirmed consistent patterns with our theory of xenophobia. Table 5 shows regression coefficients when regressing Sinophobic behaviors on the average z-score index of racial animus and perceived unacceptance of racial animus. Our theory predicts that the Sinophobic behavior would be positively correlated with racial animus and negatively correlated with perceived unacceptance of racial animus. The results confirm this pattern.

5.3 Information RCT Causal Estimates

We find our information RCT has lowered perceived unacceptance of racial animus as expected. The sign of the effect on racial animus is negative - that is, lower racial animus - but insignificant. Table 6 shows both intention-to-treat (ITT) estimates and local average treatment effect (LATE) estimates. The compliance rate iss high, 87% and the LATE estimates are

Table 6: LATE of Information RCT on ν and μ

	Dependent variable:			
	ITT		LATE	
	Racial Animus (z-score)	Perceived Unacceptance (z-score)	Racial Animus (z-score)	Perceived Unacceptance (z-score)
Whether Assigned Treatment	-0.035	-0.061^{**}		
	(0.033)	(0.029)		
Treatment			-0.040	-0.069^{**}
			(0.038)	(0.033)
Observations	2,345	2,154	2,345	2,154

Note : The compliance rate for treatment was 87%. **p<0.05;

similar to the ITT estimates.

We do not find significant ITT or LATE on xenophobic behaviors as shown by Table 7. This is most likely because the information intervention effect on racial animus and perceived unacceptance offset each other. Participants who watched the video feel less racial animus toward Chinese immigrants, possibly due to empathy, but they believe racial animus against Chinese immigrants is now more acceptable in the US.

6 Estimation Results

6.1 Density Estimation

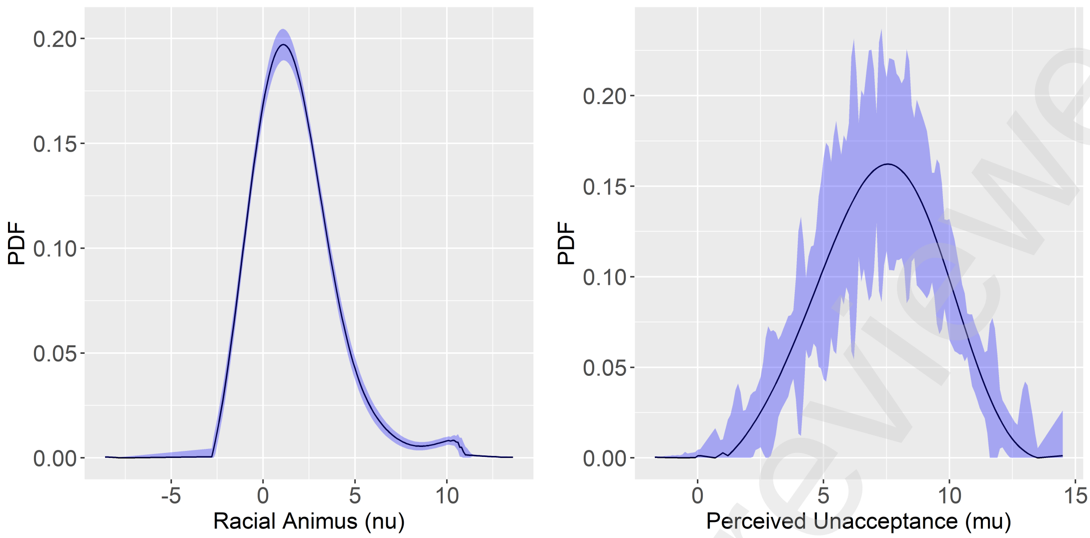
Figure 8 shows the estimated densities of racial animus and perceived unacceptance. The density of racial animus is estimated to be tighter than that of perceived unacceptance. This is likely due to a smaller correlation between proxy measures for perceived unacceptance (Table B.2). Another notable feature is that the density of racial animus is skewed to the right, while the density of the perceived unacceptance is symmetric. This means there is a small number of extreme haters, and most people show a mild degree of racial animus. On the other hand, the perception of unacceptance of racial animus is more symmetrically dispersed and is inverted-U shaped.

Table 7: Information RCT ITT and LATE

	Dependent variable:							
	ITT				LATE			
	Xenophobic Donation	Xenophobic Petition	(DG) 1(White>Chinese)	(DG) (White-Chinese)	Xenophobic Donation	Xenophobic Petition	(DG) 1(White>Chinese)	(DG) (White-Chinese)
Whether Assigned to Treatment	−0.012	−0.003	0.003	0.118				
	(0.017)	(0.012)	(0.012)	(0.407)				
Treatment					−0.014	−0.004	0.003	0.135
					(0.020)	(0.014)	(0.014)	(0.466)
Weighted Average of Dependent Variable	0.232	0.098	0.097	-0.138	0.232	0.098	0.097	-0.138
Observations	2,363	2,363	2,363	2,363	2,363	2,363	2,363	2,363

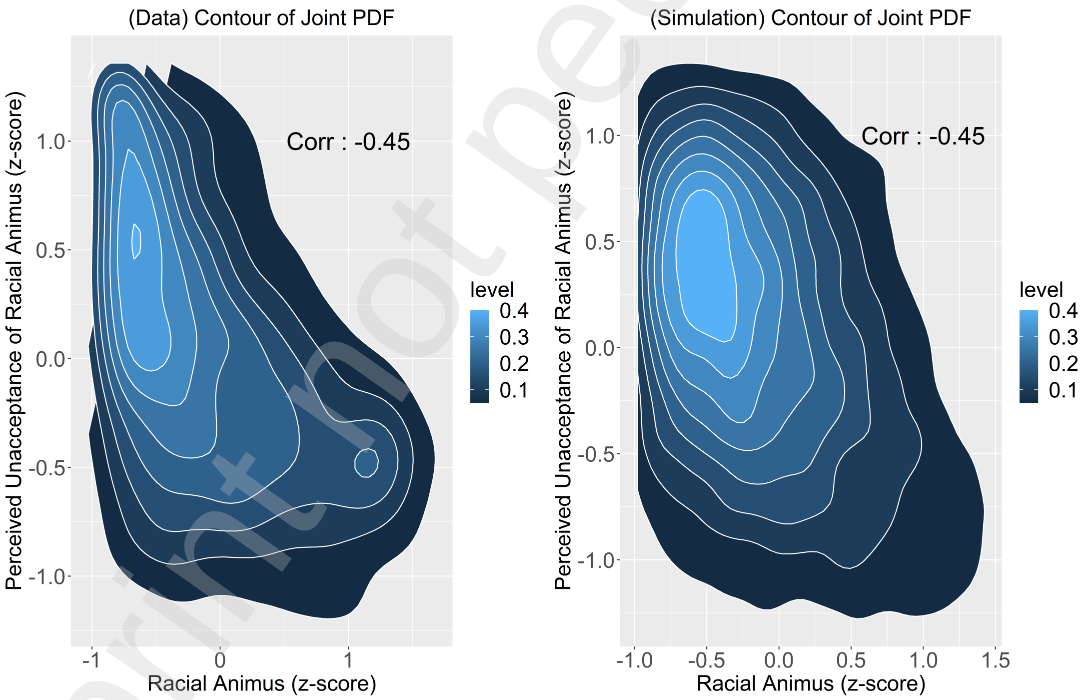
Note : The compliance rate for treatment was 87%.

Figure 8: Estimated Density of Racial Animus and Perceived Unacceptance



Note: This figure shows the estimated densities of racial animus ν and perceived unacceptance μ using the Li and Vuong (1998) deconvolution kernel estimator. The 95% confidence interval is computed from bootstrapping 100 times and is denoted as a shaded area.

Figure 9: Model Fit for Joint Density of Racial Animus and Perceived Unacceptance



Note: This figure shows the model fit of the joint density of racial animus ν and perceived unacceptance μ.

Figure 9 shows the model fit of the joint density of racial animus and perceived unacceptance. Given the Joe copula parameter estimate, the simulated data fits well the empirical joint density of average z-scores of racial animus and perceived unacceptance. Perceived unaccep-

Table 8: Structural Parameter Estimates

	Parameter Meaning	Xenophobic action Xenopho-bic Donation	Xenopho-bic Petition	(DG) 1(White>Chinese)
κ	relative importance of image concern	1.85	0.53	0.25
		(0.25)	(0.07)	(0.06)
c	location parameter for μ	-5.90	0.57	3.48
		(1.56)	(0.26)	(0.21)
β	Gumbel shock scale	8.69	4.00	3.96
		(0.82)	(0.36)	(0.12)
θ	Joe copula parameter		2.08	
			(0.11)	

Note : The standard errors are in parentheses. They are computed by bootstrapping the entire estimation procedure 100 times.

tance and racial animus are negatively correlated, with a correlation coefficient of -0.45, but are never perfectly correlated. In particular, among people with small racial animus, there is a large dispersion in the perception about unacceptance of racial animus. This means perceived unacceptance and racial animus are distinct constructs. Another notable feature is that people with high racial animus tend to perceive that racial animus is acceptable with a small variance. This may be due to a psychological tendency to have a positive self-image[34].

Figure B.1 in the Appendix shows the model fit of marginal densities of average z-scores of racial animus and perceived unacceptance. We have a reasonably good fit for the marginal densities as well.

6.2 Structural Estimates

Table 8 shows a subset of structural parameter estimates. The structural parameters (κ, c, β) are allowed to vary by xenophobic actions. Measurement equation parameter estimates are in Table B.3 in the Appendix. All standard errors are reasonably small. This mitigates the concern about identification due to the potential multiple equilibria.

Table 9 shows that the model fit is good. Every simulated moment is within the 95% confidence intervals of data moments. We match 15 moments in total.

The relative importance of image concern is captured by parameter κ and is important

[34]In the long run, there may be feedbacks between the evolution of racial animus and perceived unacceptance. However, given our cross-sectional data, studying the dynamic evolution of racial animus and perceived unacceptance is beyond the scope of this study.

Table 9: Model Fit

	Xenophobic Donation		Xenophobic Petition		(DG)1(White>Chinese)	
Moments	Data	Model	Data	Model	Data	Model
ξ_0	0.23	0.23	0.09	0.09	0.09	0.09
	[0.21,0.24]		[0.08,0.10]		[0.07,0.10]	
ξ_1	0.11	0.12	0.12	0.12	0.08	0.09
	[0.09,0.13]		[0.09,0.14]		[0.06,0.10]	
ξ_2	-0.17	-0.15	-0.05	-0.06	-0.03	-0.03
	[-0.19,-0.14]		[-0.07,-0.03]		[-0.05,-0.01]	
$P(a=1)$	0.23	0.23	0.09	0.09	0.09	0.09
	[0.21,0.25]		[0.08,0.10]		[0.08,0.10]	
$E[\widehat{v\|a=1}]-E[\widehat{v\|a=0}]$	2.02	1.95	3.41	3.24	2.51	2.35
	[1.79,2.25]		[3.01,3.81]		[2.09,2.93]	

Note : 95% CIs of data moments are in brackets. ξ_0, ξ_1, ξ_2 are regression coefficients in a linear probability model in equation 23.

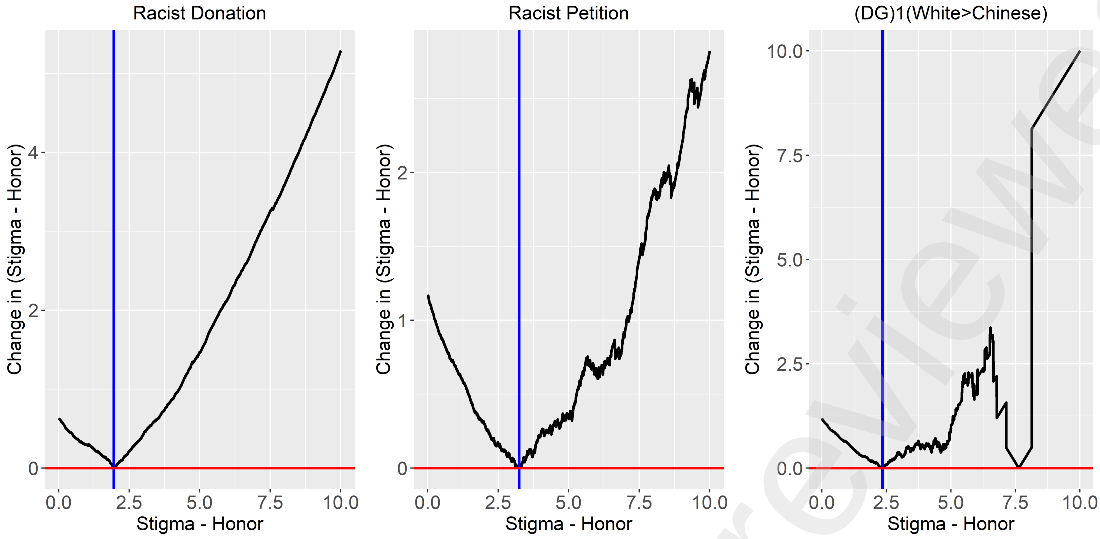
for our counterfactual analysis. It is estimated to vary sizably across different xenophobic actions. This implies the image concern may differ by xenophobic actions, possibly because each xenophobic action may have different publicity. κ was estimated to be the largest for a donation decision and the smallest for a dictator game outcome.

We examine whether there are other equilibria under our estimated structural parameters. Figure 10 shows that there are multiple equilibria under the structural parameter estimates. Each panel in Figure 10 shows the change in reputational gain $E[v|a=1]-E[v|a=0]$ after applying the fixed point mapping implied by the theory given the current reputational gain. When there is no change, shown as a tangent point on a zero-horizontal line, it means there is an equilibrium corresponding to the reputational gain. In the third panel of xenophobic behavior during the dictator games, we see another equilibrium with much higher reputational gain. For the two other xenophobic actions we consider, we do not find evidence of multiple equilibria.

6.3 Validation

We validate our structural parameter estimates by comparing our model prediction for the RCT treatment effect on xenophobic actions with the reduced-form causal estimates (Table 7). We estimate the densities of racial animus and perceived unacceptance by treatment status and using our structural parameter estimates we predict the xenophobic actions. We take the reputational gains fixed at the estimated level because we do not expect the participants to take into account the RCT effect on the reputational gain – that is, we compare the short-run

Figure 10: Evidence of Multiple Equilibria Under Structural Parameter Estimates



Note: This figure shows that there are multiple equilibria under the structural parameter estimates (for xenophobic behavior during the dictator game, titled '(DG)1(White>Chinese)'). There is no other equilibrium for xenophobic donation or xenophobic petition.

Table 10: Validation of Structural Parameter Estimates

	ITT (Model)	ITT (Data)	ITT (SE)
Xenophobic Donation	0.00	-0.01	0.02
Xenophobic Petition	0.00	0.00	0.01
Xenophobic Dictator Game	-0.01	0.00	0.01

Note: This table compares our model prediction for the intention-to-treat (ITT) estimates for xenophobic behaviors with the reduced-form ITT estimates. The third column shows the standard errors of the reduced-form ITT estimates.

prediction estimates with the reduced-form causal estimates.

Table 10 shows that we can match the reduced-form intention-to-treat (ITT) estimates. All our predicted values are within the 95% confidence intervals around the reduced-form ITT estimates. This supports the validity of our structural parameter estimates.

7 Counterfactual Analysis

We make three counterfactual predictions using our estimated structural models. First, we quantify the relative importance of intrinsic motivation versus reputational motivation in reducing xenophobic actions. Second, we predict how COVID infections affect xenophobia both in the short and in the long run. Third, we predict the effect of Fox News viewership on xenophobic actions in the short and in the long run.

We set an equilibrium selection rule because of the presence of multiple equilibria. The

Table 11: Counterfactual Prediction When Shifting Racial Animus and Perceived Unacceptance by 0.13 Standard Deviations Respectively

		shifts racial animus (v) by 0.13 SD		shifts perceived unacceptance (μ) by 0.13 SD	
		Holding (stigma - honor) fixed as baseline			
	baseline	p.p. ch	% ch	p.p. ch	% ch
Xenophobic Donation	0.23	-0.46	-2.01	-1.62	-7.10
Xenophobic Petition	0.09	-0.50	-5.60	-0.71	-7.97
Xenophobic Dictator Game	0.09	-0.58	-6.78	-0.36	-4.23
		Updating (stigma - honor) in new equilibrium			
	baseline	p.p. ch	% ch	p.p. ch	% ch
Xenophobic Donation	0.23	-0.51	-2.23	-2.54	-11.15
Xenophobic Petition	0.09	-0.74	-8.35	-1.39	-15.56
Xenophobic Dictator Game	0.09	-0.79	-9.14	-0.56	-6.49

Note: This table shows the counterfactual predictions for shifting the racial animus v and perceived unacceptance μ by 0.13 standard deviations. The 0.13 standard deviation is the difference between an average White person and average non-White, non-Black, non-Asian person (Others) (Figure 7). The top panel shows a short-run prediction holding the reputational gain fixed at the baseline level and the bottom panel shows a long-run prediction when updating the reputational gain to a new level.

rule entails choosing the equilibrium with a reputational gain closest to the baseline level. This assumption is reasonable if it is less likely to have an abrupt change in the equilibrium reputational gain.

Assumption 3 (Equilibrium Selection Rule)**.** *We choose an equilibrium whose reputational gain $E[v|a=1]-E[v|a=0]$ is closest to the baseline level.*

7.1 Relative Significance of Racial Animus and Perceived Unacceptance

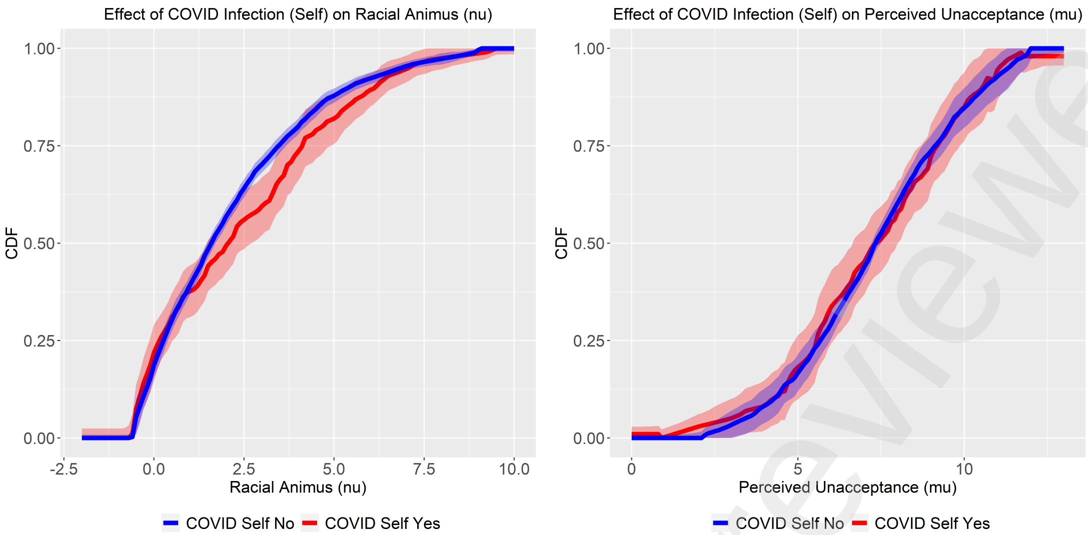
To account for the relative importance between intrinsic motivation and reputational concern, we make counterfactual predictions when shifting racial animus and perceived unacceptance distribution by 0.13 standard deviations. To give a sense of how large the 0.13 standard deviation difference is, it equals the difference between the most hostile racial group, White, and the most friendly racial group, other race (Figure 7).

Table 11 shows the counterfactual predictions. The top panel shows the short-run prediction, which holds the reputational gain at the baseline level. The bottom panel shows the long-run prediction, which updates the reputational gain to a new fixed point. Table B.4 in the Appendix summarizes the changes in the reputational gains in each counterfactual scenario. Also, we investigate the presence of multiple equilibria in any of these counterfactual computations. Figure B.4 and B.5 in the Appendix show there are multiple equilibria for xenophobic behavior during the dictator games. We pick an equilibrium following our equilibrium selection rule.

We find that, for xenophobic actions (xenophobic donation and xenophobic petition) with large relative importance for perceived unacceptance (κ), shifting perceived unacceptance μ is more effective at reducing xenophobic actions both in short and in the long run. For the xenophobic dictator game, κ is estimated to be the smallest, and, in this case, shifting the racial animus ν is marginally more effective both in short and in the long run. A much larger decrease in xenophobic donation and xenophobic petition action occurs in the long run when we shift perceived unacceptance. This is because the reputational gain becomes bigger (Table B.4), and therefore, marginal agents stop engaging in xenophobic actions due to higher reputational consequences.

We do not claim that the conclusion is generalizable to any context. With a different joint distribution of racial animus and perceived unacceptance $F(\nu, \mu)$ and different relative importance of reputational concern parameter κ, the conclusion may change. The takeaway from our analysis is that the joint density of $F(\nu, \mu)$ and the relative importance parameter κ matters for the marginal change in xenophobic action. For example, the fact that there is a thin tail of extreme haters while the perceived unacceptance is rather symmetrically distributed around the median makes the perceived unacceptance a more important margin to reduce most xenophobic actions. The publicity of xenophobic action, which can be captured by κ, is crucial as well. For a mostly private xenophobic action, reducing racial animus can be more important. If someone wants to know which margin is more important for reducing xenophobic actions, one should examine how racial animus and perceived unacceptance are distributed in society and consider the publicity of those xenophobic actions.

Figure 11: Effect of COVID Infection (Self)



Note: This figure shows the prediction on the CDF of racial animus ν and perceived unacceptance μ if everyone gets infected with COVID (COVID Self Yes) and if everyone does not get infected with COVID (COVID Self No). The COVID infection polarizes racial animus as shown by more mass at both tails for COVID Self Yes. On the other hand, COVID infection does not change the distribution of perceived unacceptance.
The prediction was made from quantile regressions in equation 5, 6. The controls include demographic variables (race, education, marital status, gender, age), state fixed effect, and proxies for pre-pandemic attitude toward Asians (whether voted for Trump in 2016, number of close Asian friends, whether a spouse is Asian, Asian shares in childhood schools). The shades show 95% confidence interval around the estimates.

Table 12: Counterfactual Predictions for Different COVID (Self) Infection Scenarios

	Holding the (stigma - honor) fixed as baseline			
	COVID (Self) Infection		Yes - No	
	No	Yes	p.p. ch	% ch
Xenophobic Donation	0.23	0.24	1.28	5.58
Xenophobic Petition	0.09	0.10	1.43	16.52
Xenophobic Dictator Game	0.08	0.09	0.88	11.24
	Updating the (stigma - honor) in new eqm			
	No	Yes	p.p. ch	% ch
Xenophobic Donation	0.23	0.21	-2.21	-9.57
Xenophobic Petition	0.12	0.11	-1.52	-12.24
Xenophobic Dictator Game	0.11	0.09	-2.15	-19.58

Note: This table shows the counterfactual predictions for when everyone gets infected with COVID and when no one gets infected with COVID. The top panel shows a short-run prediction holding the reputational gain fixed at the baseline level and the bottom panel shows a long-run prediction when updating the reputational gain to a new level.

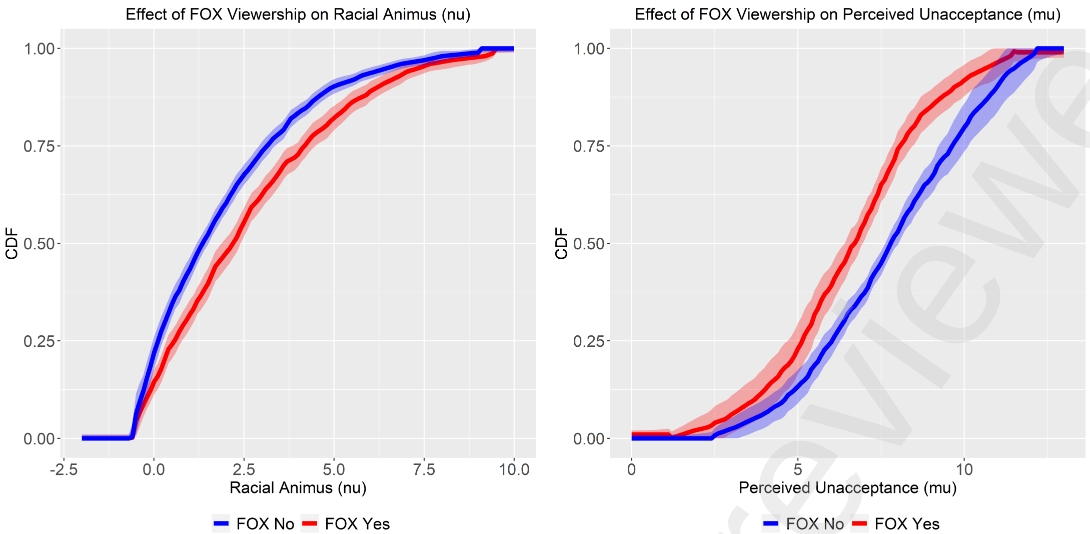
7.2 Effects of COVID-Related Experience

We examine how xenophobia could differ based on COVID infection (everyone or no one gets infected). First, we run quantile regressions (equation 5, 6) and predict the distribution of racial animus v and perceived unacceptance μ under counterfactuals. We make the conditional independence assumption that conditioning on covariates X, the COVID-related experience is independent of potential outcomes of v and μ. We control for demographic variables (race, education, marital status, gender, age), state fixed effect, and proxies for pre-pandemic attitudes towards Asians (whether one voted for Trump in 2016, one's number of close Asian friends, whether one's spouse is Asian, and one's Asian shares in childhood schools).

We find COVID infection polarizes racial animus that is shown by more mass at both tails of the distribution but only minimally changes perceived unacceptance. We also estimate the effects of other COVID-related experiences—whether someone close (family/relative/friend) to a respondent got infected with COVID and changes in work mode during the pandemic (job loss/work face-to-face/telework). Figures B.2 and B.3 in the Appendix show there is no effect from these other experiences.

Table 12 shows counterfactual predictions. In the short run, COVID infection increases xenophobic actions, as shown in the top panel. However, in the long run, COVID infection decreases xenophobic actions because there is much higher reputational gain from not engaging in these actions. This is because COVID infection increases the share of extreme haters, and therefore, xenophobic actions signal for much higher racial animus in the long run (Table B.5 in the Appendix). As a result, marginal agents choose to avoid xenophobic behaviors to be distinguished from the extreme haters who engage in xenophobic actions. Figures B.7 and B.6 in the Appendix show there is no evidence of multiple equilibria in these counterfactuals.

Figure 12: Effect of Fox News viewership



Note: This figure shows the counterfactual predictions for when everyone watches Fox News versus when everyone does not watch Fox News. Fox News increases racial animus and decreases perceived unacceptance at every percentile.

The prediction was made from quantile regressions in equation 5, 6. The controls include demographic variables (race, education, marital status, gender, age), state fixed effect, and proxies for pre-pandemic attitude toward Asians (whether voted for Trump in 2016, number of close Asian friends, whether a spouse is Asian, Asian shares in childhood schools). The shades show 95% confidence interval around the estimates.

Table 13: Counterfactual Predictions for Different Fox News Viewership

	Holding the (stigma - honor) fixed as baseline			
	FOX Viewership		Yes - No	
	No	Yes	p.p. ch	% ch
Xenophobic Donation	0.20	0.28	7.89	39.11
Xenophobic Petition	0.07	0.12	4.03	53.85
Xenophobic Dictator Game	0.07	0.10	2.74	39.32
	Updating the (stigma - honor) in new eqm			
	No	Yes	p.p. ch	% ch
Xenophobic Donation	0.21	0.28	6.83	32.33
Xenophobic Petition	0.10	0.15	5.52	57.39
Xenophobic Dictator Game	0.11	0.11	-0.19	-1.73

Note: This table shows the counterfactual prediction for when everyone watches Fox News and for when no one watches Fox News. The top panel shows a short-run prediction holding the reputational gain fixed at the baseline level and the bottom panel shows a long-run prediction when updating the reputational gain to a new level.

7.3 Fox News viewership

We extend recent literature on the effect of Fox News viewership by focusing on a question that has not been answered yet: What effect does Fox News viewership have on xenophobia? Previous papers analyzed the effect of Fox News viewership on political and social-distancing behaviors (Martin and Yurukoglu (2017b), Ananyev et al. (2021), Ash et al. (2020), Bursztyn et al. (2020), Simonov et al. (2020)).

In Appendix C, we provide evidence that Fox News associated China with the coronavirus more frequently than MSNBC from analyzing news channel transcripts between January 2020 and July 2020 (Figure C.3). For details on data cleaning, please see Appendix Section C.

Next, we show from our survey data that Fox News viewership strongly influences both racial animus and perceived unacceptance (Figure 12): it increases racial animus and decreases perceived unacceptance at every percentile. The effects are predicted using quantile regressions in equation 5, 6 with the same set of covariates as in Section 7.2.

There are a few caveats in interpreting the estimates. First, we measured Fox News viewership at the time of our survey, so people who reported watching Fox News may have started before the pandemic and may have been previously affected by its content. Second, conditional independence may be too strong an assumption for establishing causality. In that case, our estimates will include selection bias from the residual not explained by our extensive covariates, including pre-Pandemic attitude proxies.

Table 13 shows that Fox News viewership increases xenophobic actions by a large margin (39% - 54%) in the short run and (-2% - 57%) in the long run. Figure B.8, B.9 show no evidence of multiple equilibria in counterfactuals. For the xenophobic dictator game, Fox News viewership does not increase xenophobic behavior in the long run because the reputational gain under the counterfactual wherein people do not watch Fox News falls, and this causes people to engage in xenophobic action more. (Table B.6).

8 Conclusion

We present a structural model of xenophobia and estimate our model using newly developed survey instruments to identify motivations behind xenophobic actions. Our model can potentially have multiple equilibria, so we used an estimation strategy which guarantees a point identification despite this possibility. We validate our structural estimation result using the information RCT implemented during the survey.

Our model can be used to quantify the relative importance of racial animus and perceived unacceptance to reduce xenophobic actions. We find that raising perceived unacceptance is more effective than reducing racial animus at decreasing most xenophobic behaviors measured in our survey. The only exception is the dictator game, for which the relative importance of reputational motivation is estimated to be smallest; this might be because the action in the dictator game is considered private.

The reasons why shifting perceived unacceptance is more effective for changing xenophobic behaviors in our data are twofold. First, there are more switchers when we shift perceived unacceptance than when we shift racial animus. This is the first-order effect, and its size depends on the distributional shape of racial animus, perceived unacceptance, and the current location of the separating hyperplane. Second, there is a more significant change in reputational gain from xenophobic (in)action when we shift perceived unacceptance. Higher reputational gain from xenophobic (in)action makes the moderate haters halt xenophobic actions. This is the second-order effect, which determines the long-run outcome.

We get an optimistic prediction for the effect of COVID (self) infection on xenophobia. Although COVID (self) infection increases xenophobic actions in the short run, it may decrease them in the long run due to the reputational gain from xenophobic (in)action being higher. COVID (self) infections polarize racial animus and increase the extreme haters who newly engage in xenophobic behaviors. However, that increased stigma for xenophobic behaviors causes the moderate haters to avoid xenophobic behaviors in the long run over reputational concerns. It would have been difficult to make this long-run prediction if we had no structural model on xenophobia.

We find that Fox News viewership increases xenophobic behaviors by a large margin. Several papers have found significant effects of Fox News viewership on various outcomes, including political attitudes and health behaviors (Martin and Yurukoglu (2017a), Ananyev et al. (2021), Ash et al. (2020), Bursztyn et al. (2020), Simonov et al. (2020)). In our study, we find it also affects xenophobic behaviors against minorities. This reinforces the evidence on the importance of news media and calls for further studies on media policies.

Last, our study calls for future work on the determinants of racial animus and perceived unacceptance. Due to the cross-sectional nature of our data, it is infeasible to study how these two motivations form in the first place, nor can we address the possibility of any dynamic feedback effects between racial animus and perceived unacceptance. If there is any psychological bias regarding positive self-image, racial animus is likely to affect one's perceived unacceptance. Also, if there is homophily in social networks by racial animus, perceived unacceptance may negatively correlate with racial animus, as we observe in our data. Racial animus and perceived unacceptance are important drivers of xenophobic behaviors, so further work on how these two motivations are determined in a dynamic framework will enhance our understanding on how to deter xenophobia.

References

Altonji, J. G., T. E. Elder, and C. R. Taber (2005). Selection on observed and unobserved variables: Assessing the effectiveness of catholic schools. *Journal of political economy 113*(1), 151–184.

Altonji, J. G. and L. M. Segal (1996). Small-sample bias in gmm estimation of covariance structures. *Journal of Business & Economic Statistics 14*(3), 353–366.

Ananyev, M., M. Poyker, and Y. Tian (2021). The safest time to fly: pandemic response in the era of fox news. *Journal of Population Economics 34*(3), 775–802.

Ash, E., S. Galletta, D. Hangartner, Y. Margalit, and M. Pinna (2020). The effect of fox news on health behavior during covid-19. *Available at SSRN 3636762*.

Bayer, C., R. Lütticke, L. Pham-Dao, and V. Tjaden (2019). Precautionary savings, illiquid assets, and the aggregate consequences of shocks to household income risk. *Econometrica 87*(1), 255–290.

Bénabou, R. and J. Tirole (2006). Incentives and prosocial behavior. *American economic review 96*(5), 1652–1678.

Berinsky, A. J., M. F. Margolis, and M. W. Sances (2014). Separating the shirkers from the workers? making sure respondents pay attention on self-administered surveys. *American Journal of Political Science 58*(3), 739–753.

Bertrand, M. and E. Duflo (2017). Field experiments on discrimination. *Handbook of economic field experiments 1*, 309–393.

Besley, T., A. Jensen, and T. Persson (2019). Norms, enforcement, and tax evasion. Technical report, National Bureau of Economic Research.

Bisin, A., A. Moro, and G. Topa (2011). The empirical content of models with multiple equilibria in economies with social interactions. Technical report, National Bureau of Economic Research.

Bisin, A., G. Topa, and T. Verdier (2004). Religious intermarriage and socialization in the united states. *Journal of political Economy 112*(3), 615–664.

Bruins, M., J. A. Duffy, M. P. Keane, and A. A. Smith Jr (2018). Generalized indirect inference for discrete choice models. *Journal of econometrics 205*(1), 177–203.

Bursztyn, L., G. Egorov, and S. Fiorin (2020). From extreme to mainstream: The erosion of social norms. *American Economic Review 110*(11), 3522–48.

Bursztyn, L., A. Rao, C. P. Roth, and D. H. Yanagizawa-Drott (2020). Misinformation during a pandemic. Technical report, National Bureau of Economic Research.

Butera, L., R. Metcalfe, W. Morrison, and D. Taubinsky (2021). Measuring the welfare effects of shame and pride. Technical report, National Bureau of Economic Research.

Chandrasekhar, A. G., B. Golub, and H. Yang (2018). Signaling, shame, and silence in social learning. Technical report, National Bureau of Economic Research.

Cibelli, K. (2017). *The Effects of Respondent Commitment and Feedback on Response Quality in Online Surveys.* Ph. D. thesis.

Cunha, F., J. J. Heckman, and S. M. Schennach (2010). Estimating the technology of cognitive and noncognitive skill formation. *Econometrica 78*(3), 883–931.

de Paula, A. (2013). Econometric analysis of games with multiple equilibria. *Annu. Rev. Econ. 5*(1), 107–131.

Delaigle, A. and I. Gijbels (2004). Practical bandwidth selection in deconvolution kernel density estimation. *Computational statistics & data analysis 45*(2), 249–267.

DellaVigna, S., J. A. List, U. Malmendier, and G. Rao (2016). Voting to tell others. *The Review of Economic Studies 84*(1), 143–181.

Dubé, J.-P., X. Luo, and Z. Fang (2017). Self-signaling and prosocial behavior: A cause marketing experiment. *Marketing Science 36*(2), 161–186.

Elías, J. J., N. Lacetera, and M. Macis (2019). Paying for kidneys? a randomized survey and choice experiment. *American Economic Review 109*(8), 2855–88.

Flood, S., M. King, R. Rodgers, S. Ruggles, J. R. Warren, and M. Westberry (2021). Integrated public use microdata series, current population survey: Version 9.0.

Fu, C. (2014). Equilibrium tuition, applications, admissions, and enrollment in the college market. *Journal of Political Economy 122*(2), 225–281.

Glaeser, E. L. (2005). The political economy of hatred. *The Quarterly Journal of Economics 120*(1), 45–86.

Glynn, A. N. (2013). What can we learn with statistical truth serum? design and analysis of the list experiment. *Public Opinion Quarterly 77*(S1), 159–172.

Gourieroux, C., A. Monfort, and E. Renault (1993). Indirect inference. *Journal of applied econometrics 8*(S1), S85–S118.

Grigorieff, A., C. Roth, and D. Ubfal (2018). Does information change attitudes towards immigrants? representative evidence from survey experiments. *Representative Evidence from Survey Experiments (March 10, 2018).*

Hubbard, M. L., R. A. Casper, J. T. Lessler, et al. (1989). Respondent reactions to item count lists and randomized response. *Proceedings of the Survey Research Section', American Statistical Association, Washington, DC*, 544–448.

Jia, R. and T. Persson (2021). Choosing ethnicity: The interplay between individual and social motives. *Journal of the European Economic Association 19*(2), 1203–1248.

Karing, A. (2019). *Social Signaling and Health Behavior in Low-Income Countries.* Ph. D. thesis, UC Berkeley.

Karlan, D. S. and J. Zinman (2012). List randomization for sensitive behavior: An application for measuring use of loan proceeds. *Journal of Development Economics 98*(1), 71–75.

Kato, K., Y. Sasaki, and T. Ura (2021). Robust inference in deconvolution. *Quantitative Economics 12*(1), 109–142.

Li, T. and Q. Vuong (1998). Nonparametric estimation of the measurement error model using multiple indicators. *Journal of Multivariate Analysis 65*(2), 139–165.

Lu, R. and Y. Sheng (2020). From fear to hate: How a pandemic sparks racial animus in the united states. *Lu, Runjing and Sheng, Sophie Yanying, From Fear to Hate: How A Pandemic Sparks Racial Animus in the United States (July 9, 2020). 21st Century China Center Research Paper , Available at SSRN: https://ssrn.com/abstract=3646880 or http://dx.doi.org/10.2139/ssrn.3646880.*

Martin, G. J. and A. Yurukoglu (2017a). Bias in cable news: Persuasion and polarization. *American Economic Review 107*(9), 2565–99.

Martin, G. J. and A. Yurukoglu (2017b, Sep). Bias in cable news: Persuasion and polarization. *American Economic Review 107*(9), 2565–2599.

Moro, A. (2003). The effect of statistical discrimination on black–white wage inequality: estimating a model with multiple equilibria. *International Economic Review 44*(2), 467–500.

Mousa, S. (2020). Building social cohesion between christians and muslims through soccer in post-isis iraq. *Science 369*(6505), 866–870.

Nelder, J. A. and R. Mead (1965). A simplex method for function minimization. *The computer journal 7*(4), 308–313.

Oster, E. (2019). Unobservable selection and coefficient stability: Theory and evidence. *Journal of Business & Economic Statistics 37*(2), 187–204.

Paluck, E. L., R. Porat, C. S. Clark, and D. P. Green (2021). Prejudice reduction: Progress and challenges. *Annual review of psychology 72*, 533–560.

Ruggles, S., S. Flood, S. Foster, R. Goeken, J. Pacas, M. Schouweiler, and M. Sobek (2021). Ipums usa: Version 11.0.

Scacco, A. and S. S. Warren (2018). Can social contact reduce prejudice and discrimination? evidence from a field experiment in nigeria. *American Political Science Review 112*(3), 654–677.

Simonov, A., S. K. Sacher, J.-P. H. Dubé, and S. Biswas (2020). The persuasive effect of fox news: non-compliance with social distancing during the covid-19 pandemic. *National Bureau of Economic Research Working Paper*.

Stephan, W. G., O. Ybarra, and G. Bachman (1999). Prejudice toward immigrants 1. *Journal of Applied Social Psychology 29*(11), 2221–2237.

Tessler, H., M. Choi, and G. Kao (2020). The anxiety of being asian american: Hate crimes and negative biases during the covid-19 pandemic. *American Journal of Criminal Justice 45*(4), 636–646.

APPENDIX

A Proof

Proof of Proposition 1. The proof proceeds in two steps. First, there is a one-to-one mapping between the targeting moments (ξ_0, ξ_1, ξ_2) in equation 23 and the structural parameters (κ, c) given a few estimates independently estimated before Indirect Inference. Next, given the other estimates, there is a one-to-one mapping between $P(a=1)$ and β.

To see the first step, note that our estimation strategy in Section 3 identifies the joint density $\widehat{F(\nu,\mu)}$, the reputational gain $E\widehat{[\nu|a=1}] - E\widehat{[\nu|a=0}]$, and measurement equation parameters in equation 7, 8 using proxies of ν and μ. Holding the joint density and the reputational gain fixed, (κ, c) has a one-to-one mapping with a separating hyperplane in Figure 1 and therefore, a set $\{(\nu, \mu, \epsilon_1, \epsilon_0\}$ corresponding to xenophobic action $a = 1$. Given the measurement equation parameters fixed, different set $\{(\nu, \mu, \epsilon_1, \epsilon_0)|a = 1\}$ uniquely determines (ξ_0, ξ_1, ξ_2) moments. To see this, consider that the regression coefficients are functions of the second-order moments between an outcome variable a and regressors $\left\{\frac{\sum_k \tilde{Z}_k^{\nu}}{N^{\nu}}, \frac{\sum_g \tilde{Z}_g^{\mu}}{N^{\mu}}\right\}$. These second-order moments change when the separating hyperplane changes.

To see the second step, see the logit formula.

$$P(a=1) = \int_{\nu}\int_{\mu}\left\{\frac{exp\left(\frac{\nu-(\kappa\mu+c)(E[\nu|a=1]-E[\nu|a=0])}{\beta}\right)}{exp\left(\frac{\nu-(\kappa\mu+c)(E[\nu|a=1]-E[\nu|a=0])}{\beta}\right)+1}\right\}dF(\nu,\mu). \tag{24}$$

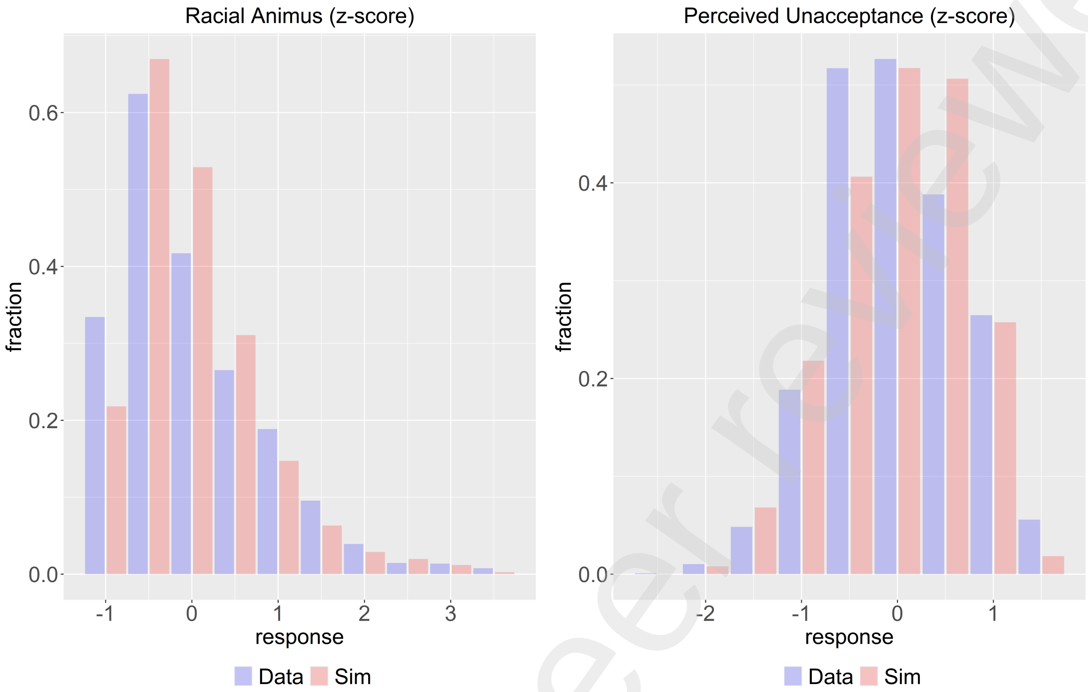
Holding the reputational gain $E[\nu|a=1] - E[\nu|a=0]$, joint density $F(\nu,\mu)$, structural parameters (κ, c) fixed, β has a one-to-one mapping with $P(a=1)$.

This concludes the proof.

□

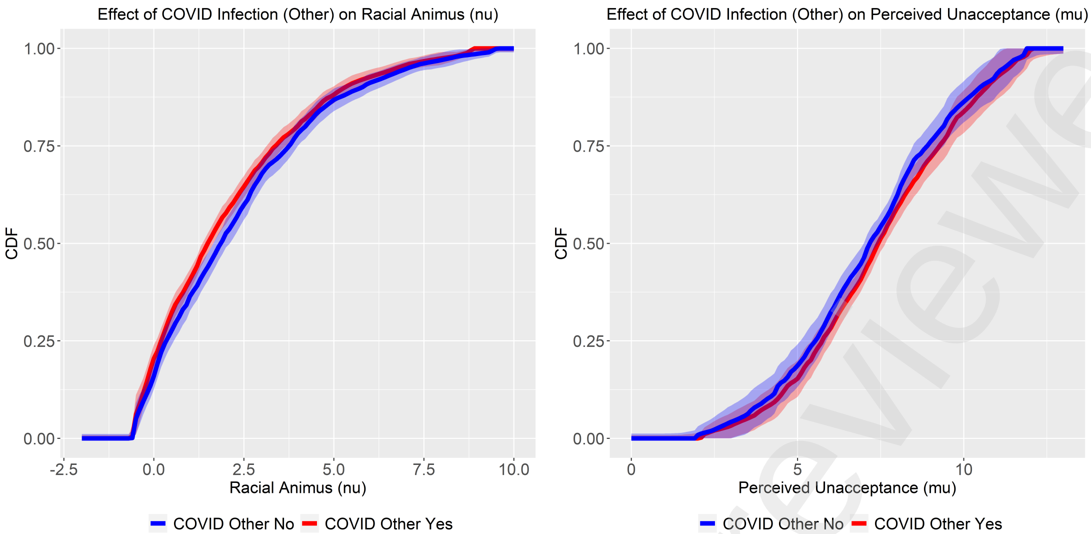
B Additional Figures and Tables

Figure B.1: Model Fit for Average Z-scores of Racial Animus and Perceived Unacceptance



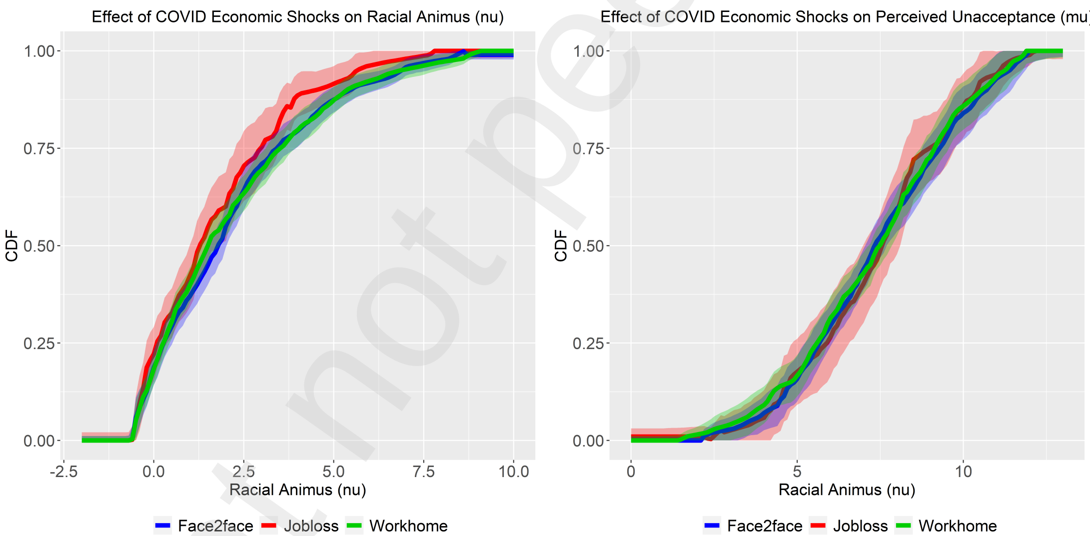
Note: This figure shows the model fit for average z-scores of racial animus and perceived unacceptance.

Figure B.2: Effect of Others' COVID Infection



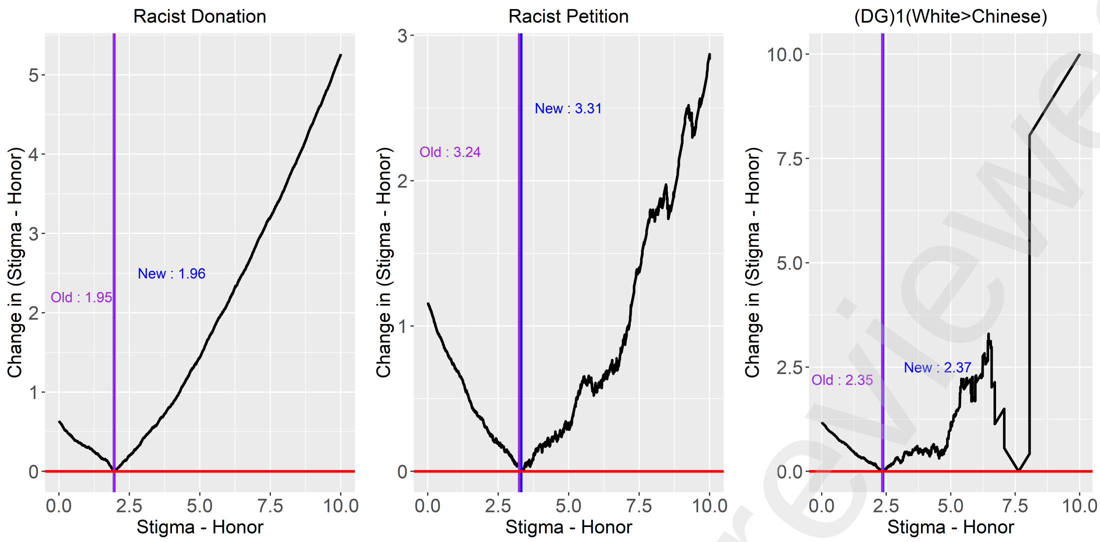
Note: This figure shows close ones', defined as either family, friends, or relatives, COVID infection on racial animus and perceived unacceptance.

Figure B.3: Effect of Economic Shocks during the Pandemic



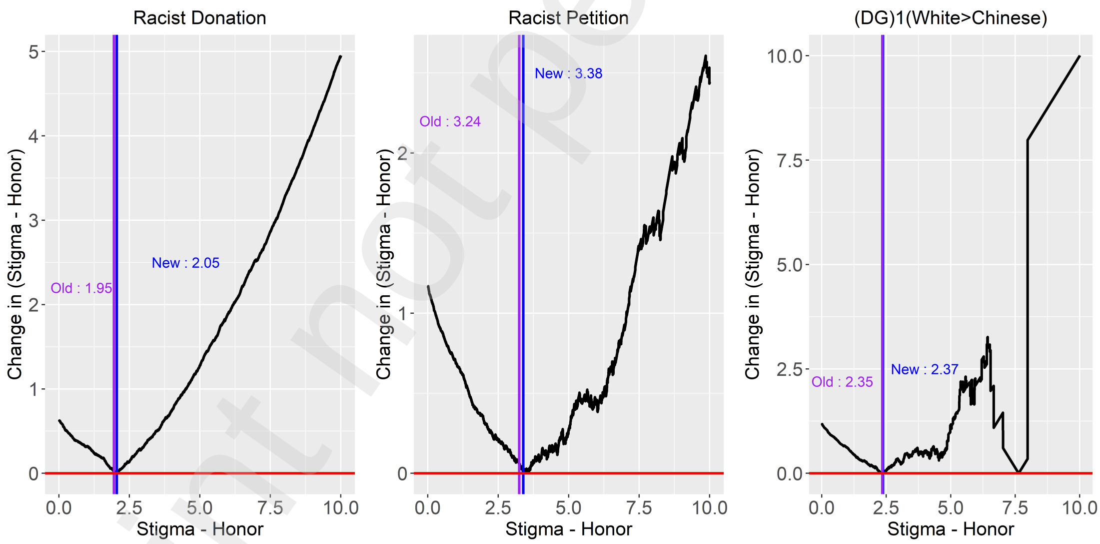
Note : This figure shows the effect of economic shocks (job loss / work face-to-face / telework) on racial animus and perceived unacceptance.

Figure B.4: Equilibrium Selection for Counterfactual 7.1 : Shift ν



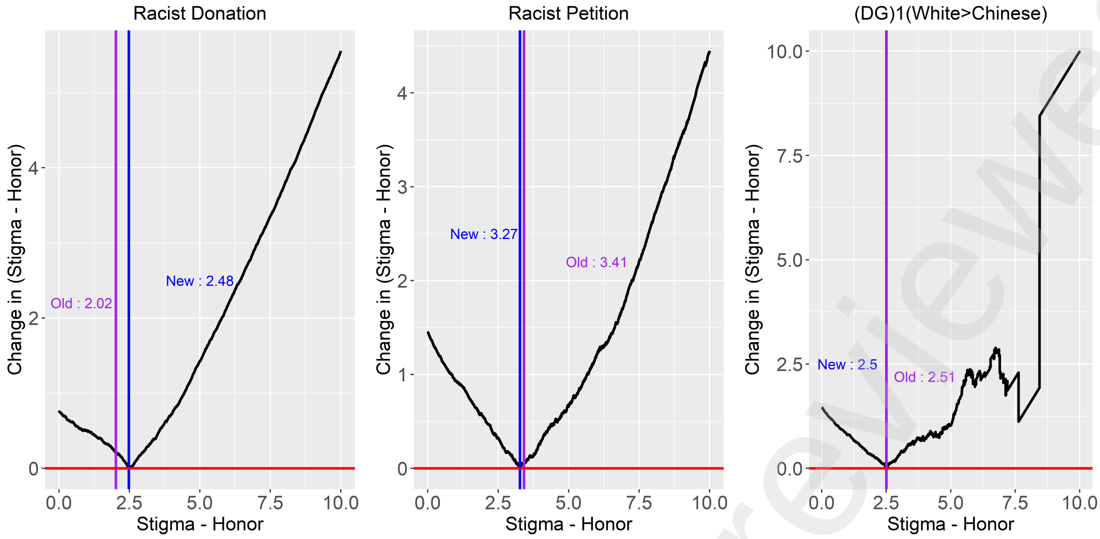
Note: This figure shows that there are multiple equilibria (for xenophobic behavior during the dictator game, titled '(DG)1(White>Chinese)') in counterfactual 7.1 shifting ν by 0.13 standard deviation. We follow our equilibrium selection rule to pick an equilibrium whose reputational gain is closest to our baseline level. There is no other equilibrium for xenophobic donation and xenophobic petition.

Figure B.5: Equilibrium Selection for Counterfactual 7.1 : Shift μ



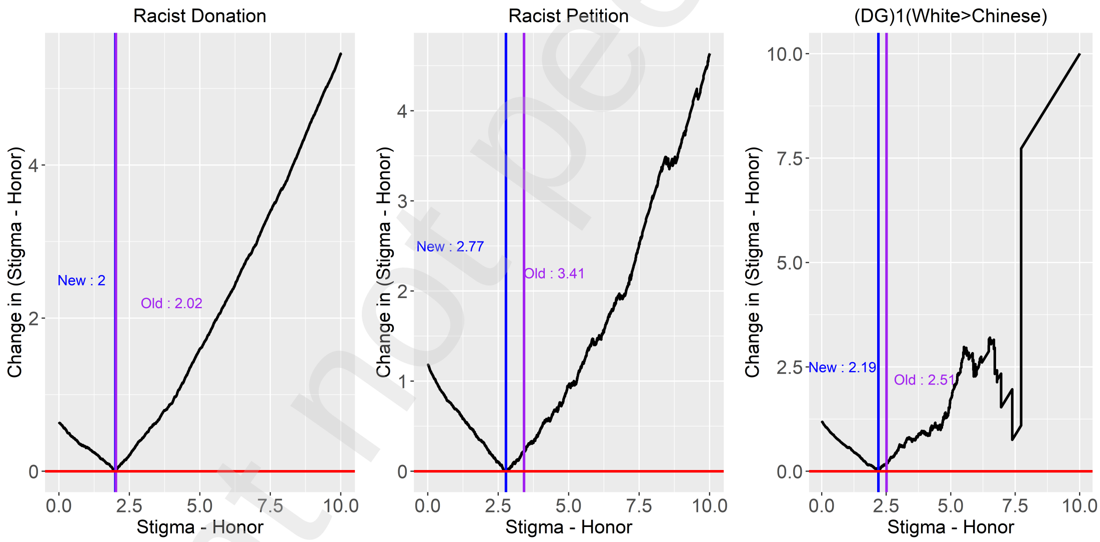
Note: This figure shows that there are multiple equilibria (for xenophobic behavior during the dictator game, titled '(DG)1(White>Chinese)') in counterfactual 7.1 shifting μ by 0.13 standard deviation. We follow our equilibrium selection rule to pick an equilibrium whose reputational gain is closest to our baseline level. There is no other equilibrium for xenophobic donation and xenophobic petition.

Figure B.6: Equilibrium Selection for Counterfactual 7.2 : COVID Infection (Self) Yes



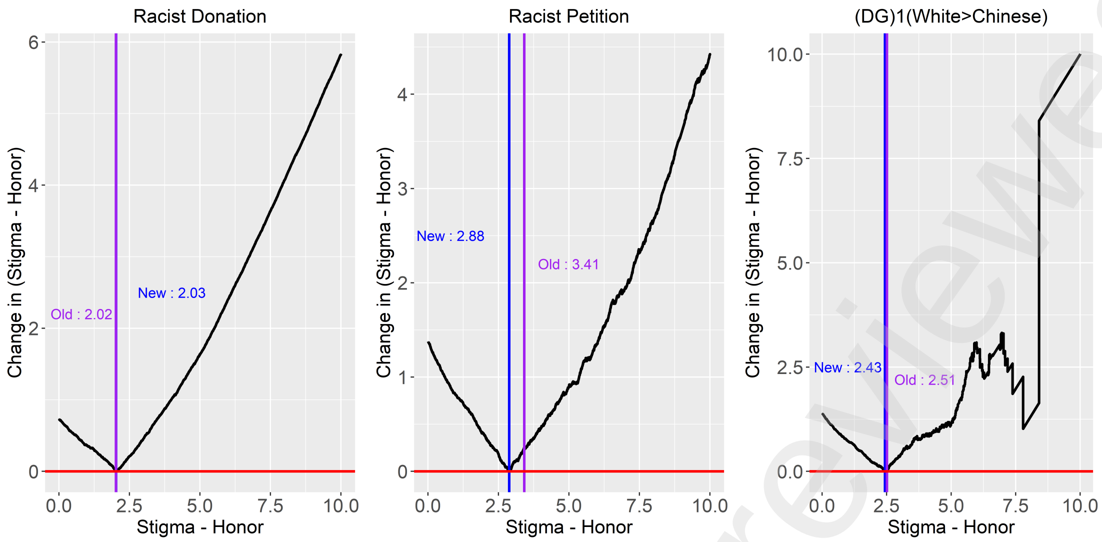
Note: This figure shows that there are no other equilibria in counterfactual 7.2 for when everyone gets infected with COVID.

Figure B.7: Equilibrium Selection for Counterfactual 7.2 : COVID Infection (Self) No



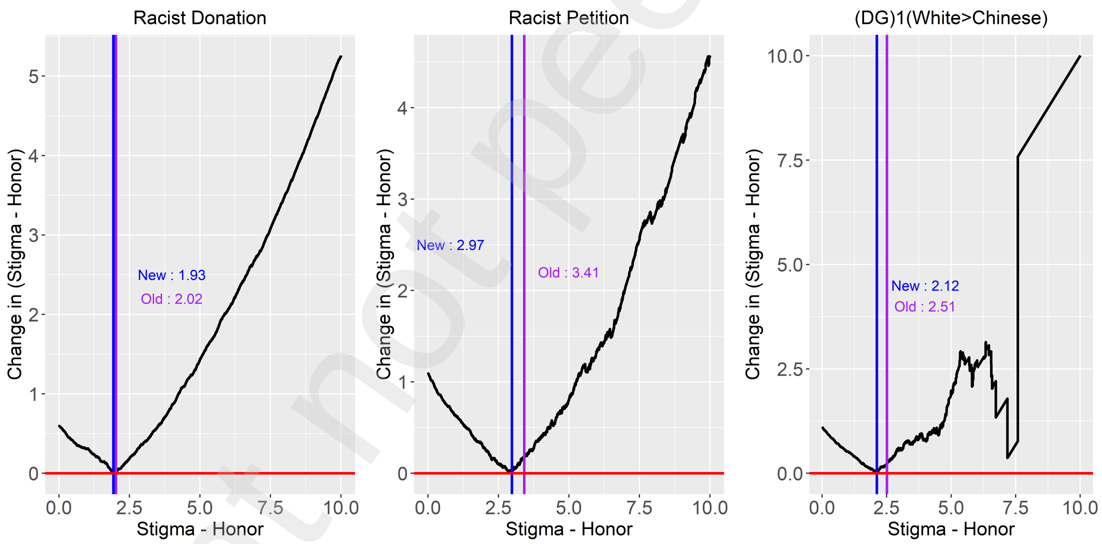
Note: This figure shows that there are no other equilibria in counterfactual 7.2 for when no one gets infected with COVID.

Figure B.8: Equilibrium Selection for Counterfactual 7.3 : FOX Yes



Note: This figure shows that there are no other equilibria in counterfactual 7.3 for when everyone watches Fox News.

Figure B.9: Equilibrium Selection for Counterfactual 7.3 : FOX No



Note: This figure shows that there are no other equilibria in counterfactual 7.3 for when no one watches Fox News.

Table B.1: Internal consistency of proxies for ν

	acceptance	warmth	schoolRight	healthHazard	dislike
acceptance					
warmth	0.76***				
schoolRight	0.51***	0.42***			
healthHazard	0.48***	0.40***	0.48***		
dislike	0.68***	0.56***	0.41***	0.35***	
hatred	0.61***	0.52***	0.37***	0.30***	0.75***

Note: This table shows the correlation between proxies for ν. As consistent with a factor model, every proxy is highly correlated with each other. $***$ means the p-value is less than 0.1%.

Table B.2: Internal consistency of proxies for μ

	reduceChineseImm	racistGoodRelation	ChinaVirusCriticism
reduceChineseImm			
racistGoodRelation	0.30***		
ChinaVirusCriticism	0.27***	0.19***	
restrictRights	0.24***	0.13***	0.26***

Note: This table shows the correlation between proxies for μ. As consistent with a factor model, every proxy is highly correlated with each other. $***$ means the p-value is less than 0.1%.

Table B.3: Measurement Equation Parameter Estimates

	α_0	α_1	$\sigma^2_{\epsilon^{\nu}_k}, \sigma^2_{\epsilon^{\mu}_g}$
acceptance	0	1	1.03
	(0)	(0)	(0.14)
warmth	0.94	0.92	1.82
	(0.06)	(0.02)	(0.15)
schoolRight	0.43	0.58	3.93
	(0.07)	(0.04)	(0.22)
healthHazard	1.59	0.69	6.71
	(0.1)	(0.04)	(0.3)
dislike	-0.24	0.83	2.7
	(0.06)	(0.03)	(0.21)
hatred	-0.26	0.68	2.75
	(0.05)	(0.03)	(0.21)
reduceChineseImm	0	1	4.68
	(0)	(0)	(0.49)
racistGoodRelation	-0.45	0.73	6.41
	(0.78)	(0.11)	(0.35)
ChinaVirusCriticism	1.18	0.69	7.19
	(0.67)	(0.09)	(0.31)
restrictRights	1.65	0.68	9.04
	(0.66)	(0.09)	(0.42)

Note: This table shows the estimates for measurement equation parameters in equation 7, 8. The anchor variables are 'acceptance' and 'reduceChineseImm', whose α_0 is normalized to 0 and α_1 is normalized to 1. The standard errors computed from bootstrapping the sample 100 times are in parenthesis.

Table B.4: Reputational Gain, $E^*[v|a=1] - E^*[v|a=0]$, in Counterfactual 7.1

	baseline	shifts racial animus ν by 0.13 SD counterfactual	shifts perceived unacceptance μ 0.13 SD counterfactual
Xenophobic Donation	1.95	1.96	2.05
Xenophobic Petition	3.24	3.31	3.38
Xenophobic Dictator Game	2.35	2.37	2.37

Note : This table shows the reputational gain in Section 7.1. Reputational gain is higher when perceived unacceptance μ is shifted. This is why shifting perceived unacceptance μ is more effective at reducing most xenophobic behaviors in the long-run.

Table B.5: Reputational Gain, $E^*[v|a=1] - E^*[v|a=0]$, in Counterfactual 7.2

		COVID (Self) Infection	
		Yes	No
	baseline	counterfactual	counterfactual
Xenophobic Donation	2.02	2.48	2
Xenophobic Petition	3.41	3.27	2.77
Xenophobic Dictator Game	2.51	2.50	2.19

Note : This table shows the reputational gain in Section 7.2. COVID infection polarizes racial animus, and raises the reputational gain when abstaining from xenophobic behaviors. This is why COVID infection decreases xenophobic behaviors in the long run.

Table B.6: Reputational Gain, $E^*[v|a=1] - E^*[v|a=0]$, in Counterfactual 7.3

		FOX Viewership	
		Yes	No
	baseline	counterfactual	counterfactual
Xenophobic Donation	2.02	2.03	1.93
Xenophobic Petition	3.41	2.88	2.97
Xenophobic Dictator Game	2.51	2.43	2.12

Note : This table shows the reputational gain in Section 7.3. For xenophobic dictator game, reputational gain is higher under Fox viewership. This leads to a small decrease in xenophobic behavior in the long run.

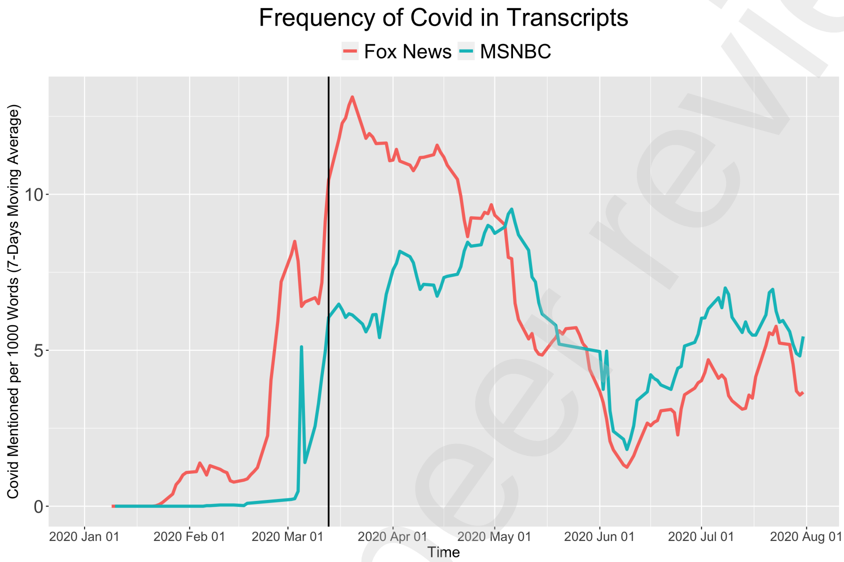
C Text Analysis of Fox News and MSNBC Transcripts

We provide the evidence that the Fox News associated China more frequently with coronavirus than MSNBC. Our evidence is consistent with Ananyev et al. (2021) Figure 2, which used a subset of our data and slightly different sample selection. Other recent papers on the Fox News coverage include Martin and Yurukoglu (2017b), Ash et al. (2020), Bursztyn et al. (2020), and Simonov et al. (2020); however, they focused on different outcome variables, such as political behavior and social distancing behavior.

We downloaded all available transcripts for Fox News and MSNBC from LexisNexis, ranging from Jan 1, 2020 to July 31, 2020. LexisNexis may not cover all shows for both channels, so we restrict our analysis to the top-5 shows for Fox News and MSNBC. For Fox News, we chose Tucker Carlson Tonight, Hannity, Ingraham Angle, Special Report with Bret Baier, and The Five. For MSNBC, the top-5 shows are The Rachel Maddow Show, The Last Word with Lawrence O'Donnell, Deadline: White House, The Beat with Ari Melber, and All In with Chris Hayes. We have done analysis with both the full sample and the top-5 sample, and the results are similar. So we only show results for the top-5 sample. We compute the frequencies of words related to China or Coronavirus and the co-occurrence of China and Coronavirus. Then, we smooth the time series using a 7-days moving average.

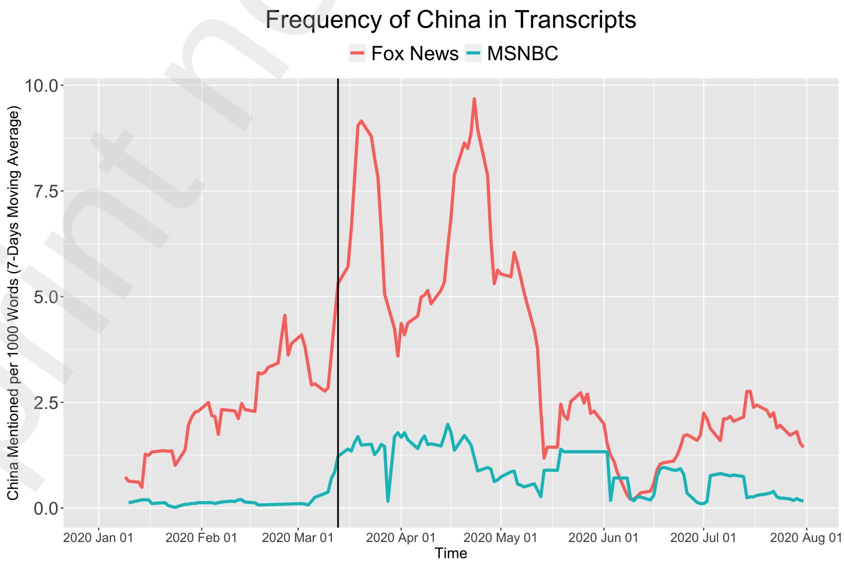
Compared to MSNBC, Fox News has mentioned China at a higher frequency in its top-5 shows (C.2) and is more likely to associate China with Coronavirus (Figure C.3) throughout our sample period. Fox News mentioned COVID more frequently at the beginning of the Pandemic than MSNBC.

Figure C.1: Frequency of Covid in Transcripts (7-Days Moving Average)



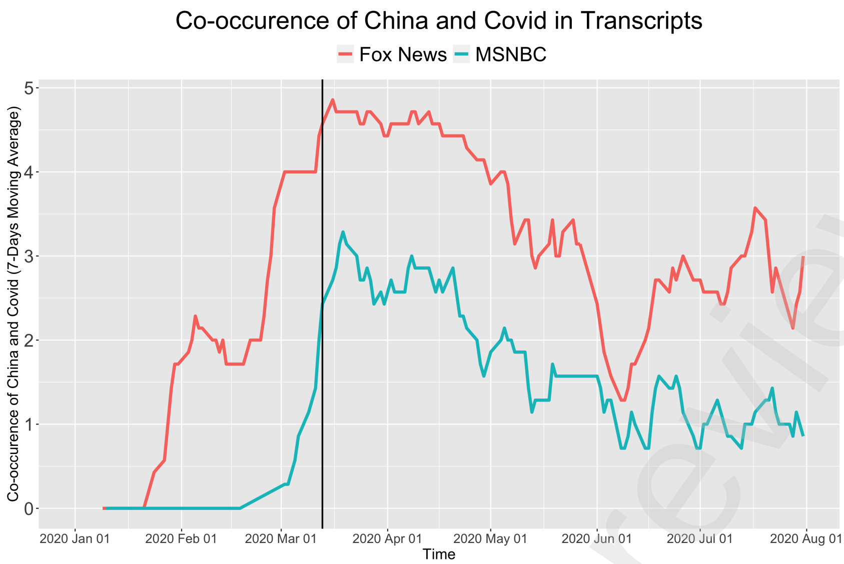
Note: This figure shows how many times a Covid-related word appears in 1000 words every day for the top-5 shows of Fox News and MSNBC.

Figure C.2: Frequency of China in Transcripts (7-Days Moving Average)



Note: This figure shows how many times a China-related word appears in 1000 words every day for the top-5 shows of Fox News and MSNBC.

Figure C.3: Co-occurrence of China and Covid in Transcripts (7-Days Moving Average)



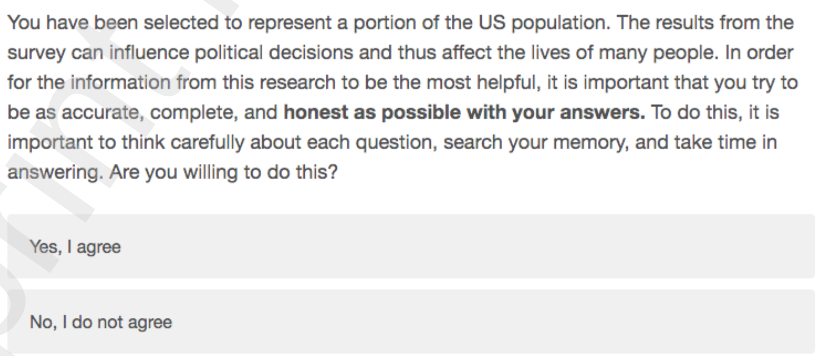
Note: This figure shows how many times both China and Covid appear in the same show every day for the top-5 shows of Fox News and MSNBC.

D Survey Questionnaire

This section shows key questions in our survey. For full survey questionnaire screenshots, see our online appendix. You can take our survey from the following link.
https://jhukrieger.co1.qualtrics.com/jfe/form/SV_0wFTvyUFb9nP1NY

D.1 Soft Commitment

We inserted a soft commitment question at the beginning of the survey, following a recommendation by Cibelli (2017).


You have been selected to represent a portion of the US population. The results from the survey can influence political decisions and thus affect the lives of many people. In order for the information from this research to be the most helpful, it is important that you try to be as accurate, complete, and **honest as possible with your answers.** To do this, it is important to think carefully about each question, search your memory, and take time in answering. Are you willing to do this?

Yes, I agree

No, I do not agree

Figure D.1: Soft commitment question

D.2 Attention Check Screener Questions

We included two attention check questions. The first attention check question asks about current feelings but careful readers will choose the 'None of the above' option only as requested in the question. The second attention check question asks about the device used for the survey but careful readers will choose 'Other' as requested.

Before we proceed, we have a question about how you are feeling.

Recent research on social preference shows that preferences are affected by context. Differences in feelings, knowledge, experience and environment can all possibly affect people's preferences and choices. It is crucial to our study that you actually take the time to read the questions. So the purpose of asking this question is to see whether you read the full instructions. Please go ahead and only check "None of the above" option as your answer, no matter how you are currently feeling. Thank you very much.

Please check all the words that describe how you are currently feeling.

Happy	Bored	Excited
Neutral	Suspicious	Anxious
Peaceful	Sad	None of the above

Figure D.2: First attention check question

We want to ask about the device you are using to participate in this survey.

Some research says the survey mode can affect the survey responses. It is very important to have high-quality survey responses to obtain scientific results. The purpose of this question is to see whether you carefully read the full question. Please ignore the question and select "Other", regardless of the device you are using. Thank you very much.

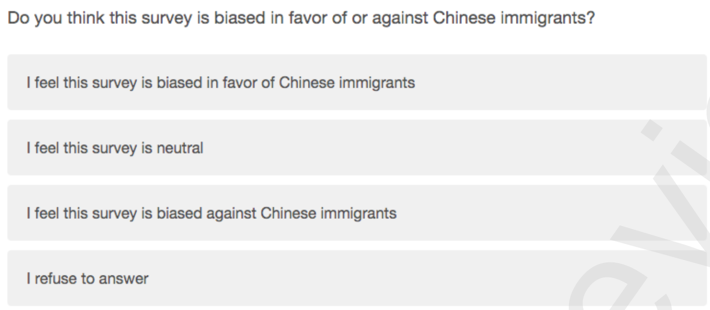
Please choose the device you are using to participate in this survey.

- Desktop computer
- Laptop
- Tablet
- Mobile phone
- Other

Figure D.3: Second attention check question

D.3 Surveyor Demand Effect Question

We inserted a question at the end of our survey to ask whether participants found our survey biased in favor of, or against Chinese immigrants. We drop the sample who answered our survey looked biased in either direction because their responses may not be honest.


Do you think this survey is biased in favor of or against Chinese immigrants?

I feel this survey is biased in favor of Chinese immigrants

I feel this survey is neutral

I feel this survey is biased against Chinese immigrants

I refuse to answer

Figure D.4: Question to Check Any Surveyor Demand Effect

D.4 Measurement of Sinophobic Behavior

This section explains our survey questions to measure xenophobic actions.

D.4.1 Donation question

We gave a short description of two organizations with opposing attitudes toward Chinese students and scholars. The donation to Organization A is coded as a Sinophobic behavior. The order of the donation choice was randomized to remove any order effect and surveyor demand effect.

D.4.2 Petition question

We asked if participants want to sign any of the petitions below. The decision to sign Petition 2 was coded as a Sinophobic behavior. The order of the petition choice option was randomized to remove any order effect and surveyor demand effect.

Suppose you can authorize us to donate $1 to any of the organizations below. Which organization would you like to authorize us to donate to? You don't have to pay anything if you decide to authorize.

Organization A is a think tank, which claimed that students and exchange scholars from China represent a great risk to the United States through their spying activities. **Organization A** advocates that the U.S. should restrict the entry of Chinese students and researchers.

Organization B is a think tank, which wrote a rebuttal policy report to the claim of Organization A. **Organization B** asserts that Organization A's claim is ungrounded and the Chinese students and researchers should not receive more penalty in immigration.

I'd like to authorize a $1 donation to **Organization A**.

I'd like to authorize a $1 donation to **Organization B.**

Figure D.5: Donation question to measure Sinophobic behavior

Suppose there are two petitions, as described below. Would you like to sign any of the petitions?

Petition 1. Please Protect Chinese Immigrants' Safety and Rights

Many Chinese immigrants in the US are facing severe risks of being victims of hate crimes or discrimination, as a result of COVID-19 related fear. We should remember that the pandemic is <u>**not**</u> the fault of Chinese immigrants living in the US.

"We, the undersigned, call on the United States Congress and President of the United States to ensure the physical safety of Chinese immigrants as well as to protect their rights from discrimination"

Petition 2. Please Protect Our Country From Chinese Threats

From the COVID-19 pandemic, we have witnessed how the Chinese threatened our country's safety and prosperity. The Chinese immigrants bring <u>**no**</u> good to our country. It is time to reconsider whether it is beneficial to accept Chinese immigrants to the US.

"We, the undersigned, call on the United States Congress and President of the United States to review the current immigration policy for the Chinese and to continue making best efforts to protect our citizens' safety and interests from Chinese Threats."

Yes, I want to sign **Petition 2. Please Protect Our Country From Chinese Threats.**

Yes, I want to sign **Petition 1. Please Protect Chinese Immigrants' Safety and Rights.**

No, I do not want to sign any petition.

Figure D.6: Petition question to measure Sinophobic behavior

D.4.3 Dictator game

Every participant played a dictator game twice with a Chinese immigrant and White American. We randomized the order of the partners to remove any order effect.

We coded as a Sinophobic behavior if a participant shared more money with a White American. We use this dummy variable as a main measure of xenophobic behavior instead of the share difference because our model is to explain a discrete action. For robustness, in Table 5, we include the result using the share difference as an outcome variable and obtained qualitatively similar result to when we use a dummy variable as an outcome variable.

Now, you will be **randomly** matched with **two people** recruited for this study and you will play a game **twice** with your matched partners. All of your partners are currently living in the US.

You may receive extra rewards based on your responses.

Figure D.7: Introduction to the dictator game

This is your first game. You are matched with the following person.

Name: Haozheng

You are given a lottery to win an extra reward of 100SB (=$1), which can be divided between you and your partner. **10% of survey participants will win the lottery.**

If you win the lottery, how much would you like to give to your partner? If you win, you will be **actually** paid 100SB net of your answer. For example, if you give 50SB to your partner and if you are selected, then you will be paid 50SB (=100SB - 50SB).

Your answer will not affect your probability of winning the lottery.
Please move the slider below to enter your amount to **give** to your partner.

0 10 20 30 40 50 60 70 80 90 100

Amount to your partner (in SB)

Figure D.8: Dictator game with a Chinese immigrant


This is your second game. You are matched with the following person.

Name: Peter

You are given a lottery to win an extra reward of 100SB (=$1), which can be divided between you and your partner. ***<u>10% of survey participants will win the lottery.</u>***

If you win the lottery, how much would you like to give to your partner? If you win, you will be ***actually*** *paid 100SB net of your answer. For example, if you give 50SB to your partner and if you are selected, then you will be paid 50SB (=100SB - 50SB).*

<u>Your answer will not affect your probability of winning the lottery.</u>
Please move the slider below to enter your amount to ***give*** *to your partner.*

0 10 20 30 40 50 60 70 80 90 100

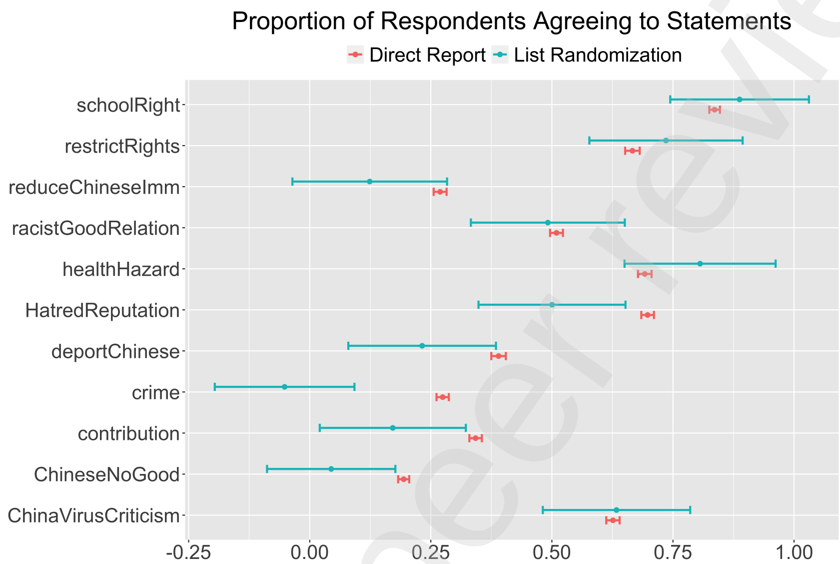
Amount to your partner (in SB)

Figure D.9: Dictator game with a White American

FOR ONLINE PUBLICATION : "Structural Analysis of Xenophobia" by Huan Deng and Yujung Hwang

A Additional Tables and Figures

Figure A.1: Test of Social Desirability Bias using List Randomization (Full Statements)



Note: This figure shows the social desirability test using every statement included in the survey.

The statements not included into analysis because of the evidence of social desirability bias are summarized in Table A.1

Table A.1: Survey Instruments Not Included In Our Analysis

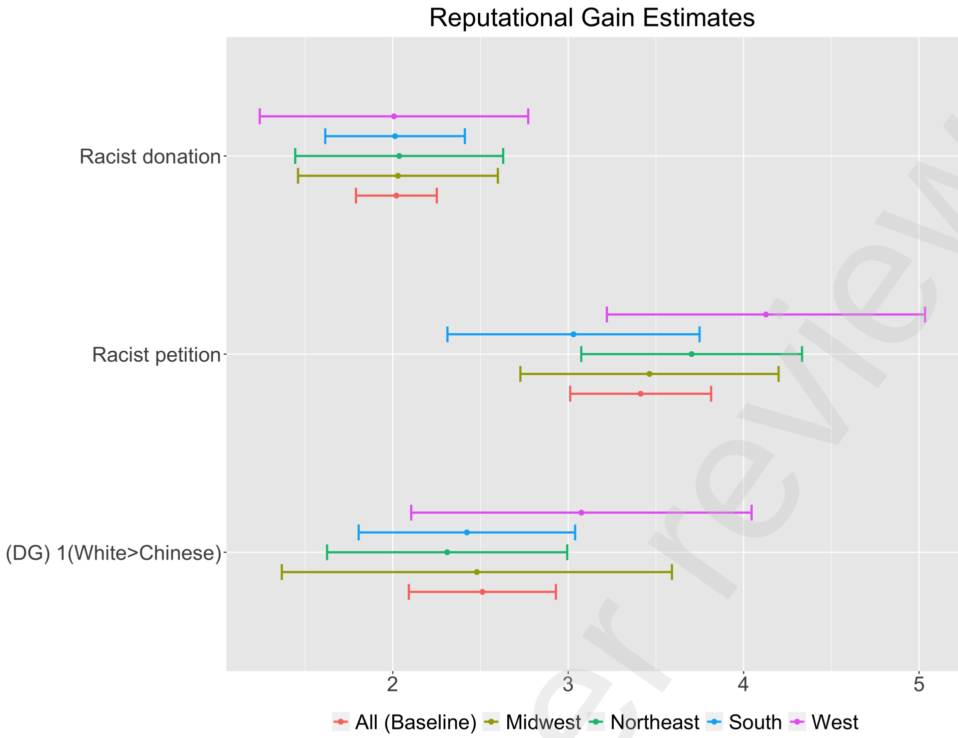
Anti-Chinese Racial Animus	
Question	Please indicate your agreement with each of the following statements concerning immigration from China. (Slider scale from 0(strongly disagree) to 100(strongly agree))
Statement	• Chinese immigrants get more from this country than they contribute. • Chinese immigrants are contributing to the increase in crime in the US.
Perceived Unacceptance of Racial Animus	
Question	Please indicate your agreement with each of the following statements concerning the attitudes of **typical American citizens (below referred to as "people").** (Slider scale from 0(strongly disagree) to 100(strongly agree))
Statement	• Even though someone publicly says he/she dislikes Chinese immigrants, the person can still maintain good social relationships with most people. • Expressing hatred against Chinese immigrants harms one's social reputation. • People will appreciate it if someone states, "Chinese immigrants bring no good to the US!" • It is socially acceptable to petition to deport Chinese immigrants if they have any Chinese government connections.

Note : This table shows the list of survey instruments not included in our analysis because of the evidence of social desirability bias as shown in Figure A.1.

B Robustness Check on a Single Equilibrium Assumption

This section reports supportive evidence of Assumption 1. We examined whether the reputational gains vary across different US regions. Figure B.1 shows that the reputational gains from different US regions are not statistically different from the reputational gain estimated from all regions. Therefore, we assume that the whole data was generated from a single equilibrium.

Figure B.1: Robustness checks whether equilibria can be different across the US regions



Note: This figure is to check whether the reputational gains are different across different US regions. We found the reputational gains are not statistically different across the US regions. This supports our Assumption 1 that the entire data corresponds to a single equilibrium.

C Robustness Check about RCT Treatment Effect on Social Desirability Bias

We examined whether RCT treatment changes social desirability bias later when respondents answer questions about either racial animus or perceived unacceptance of racial animus. We do not find evidence of change in social desirability bias by RCT treatment status. Figure C.1 repeats the test described in Section 4.1 by RCT treatment. For both treated and control groups, the means from the List randomization are not statistically different from the means from the direct report. This allows us to interpret the difference in proxy responses stemmed from the difference in latent variables instead of change in measurement errors.

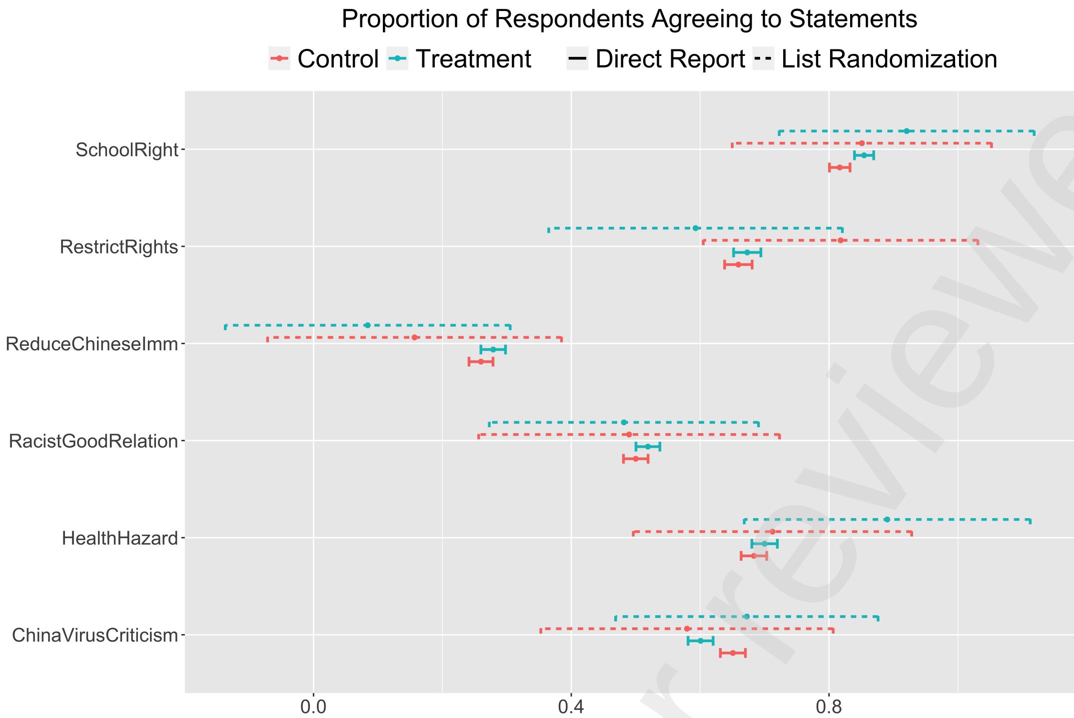


Figure C.1: List Randomization Test by RCT Treatment

D Evidence on Sample Selection

This section presents descriptive statistics about the sample who got screened out for either failure to pass the attention check questions or for their mention about bias in our survey. We found our final sample is different from the dropped sample in multiple dimensions. Importantly, we found the evidence that the screened out sample shows higher racial animus and lower perceived unacceptance, so sample selection makes our final sample less xenophobic. Sample who failed the attention check question spent less time on response which is shown by smaller 25th, median, 75th response time in Figure D.1.

Table D.1 shows the means and sds of key demographic variables by screen status. *, **, *** indicates the p-values to test whether the means are different from those of final sample. Figure D.1 shows the response time in the module asking about racial animus and perceived unacceptance. Figure D.2 shows the average z-score of racial animus and perceived unacceptance. The group who failed the first attention check question is screened out before starting the module on racial animus and perceived unacceptance, so the group is omitted in these graphs.

Table D.1: Descriptive Statistics about Sample Selection

	Fail Attn Check 1	Fail Attn Check 2	Mention Bias	Final Sample
Male	0.43	0.44	0.45	0.45
	(0.5)	(0.5)	(0.5)	(0.5)
18-29 years old	0.22***	0.17*	0.26***	0.19
	(0.41)	(0.37)	(0.44)	(0.39)
30-59 years old	0.52***	0.53***	0.57	0.58
	(0.5)	(0.5)	(0.5)	(0.49)
60-70 years old	0.26*	0.3***	0.17***	0.24
	(0.44)	(0.46)	(0.38)	(0.43)
High School or Below	0.4**	0.35	0.38	0.37
	(0.49)	(0.48)	(0.48)	(0.48)
Some College	0.27	0.27	0.27	0.28
	(0.44)	(0.44)	(0.44)	(0.45)
College	0.34*	0.38	0.36	0.36
	(0.47)	(0.49)	(0.48)	(0.48)
White	0.77***	0.81	0.81	0.8
	(0.42)	(0.39)	(0.39)	(0.4)
Black/African American	0.15***	0.12	0.1	0.11
	(0.36)	(0.32)	(0.3)	(0.31)
Others	0.07***	0.07**	0.09	0.09
	(0.26)	(0.25)	(0.28)	(0.28)
Married	0.5	0.54**	0.49	0.5
	(0.5)	(0.5)	(0.5)	(0.5)
\$0˜\$38754	0.38***	0.31	0.32	0.32
	(0.49)	(0.46)	(0.47)	(0.47)
\$38755˜\$73978	0.25***	0.28**	0.27	0.31
	(0.43)	(0.45)	(0.44)	(0.46)
\$73979˜\$129066	0.21***	0.22	0.27	0.24
	(0.41)	(0.42)	(0.44)	(0.43)
\$129067+	0.16**	0.18***	0.14	0.14
	(0.37)	(0.39)	(0.35)	(0.34)
Sample Size	5454	1815	360	2363

Note : This table summarizes how the screened samples are different from our final sample. 'Fail Attn Check 1' and 'Fail Attn Check 2' are the groups who got screened out from the first and second attention check question. 'Mention Bias' is the group who said our survey looked biased in either direction. 'Final Sample' is the sample who passed all selection criteria and was used for our analysis. The standard deviations are in parentheses. *, **, *** denotes the p-values to test whether the means are different from that of final sample. * means p<0.10, ** means p<0.05, *** means p<0.01

Figure D.1: Response Time

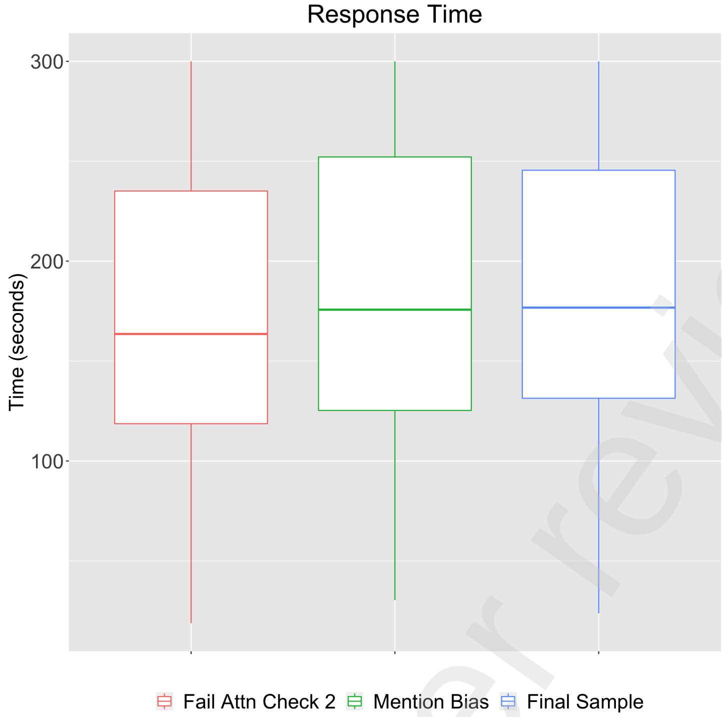
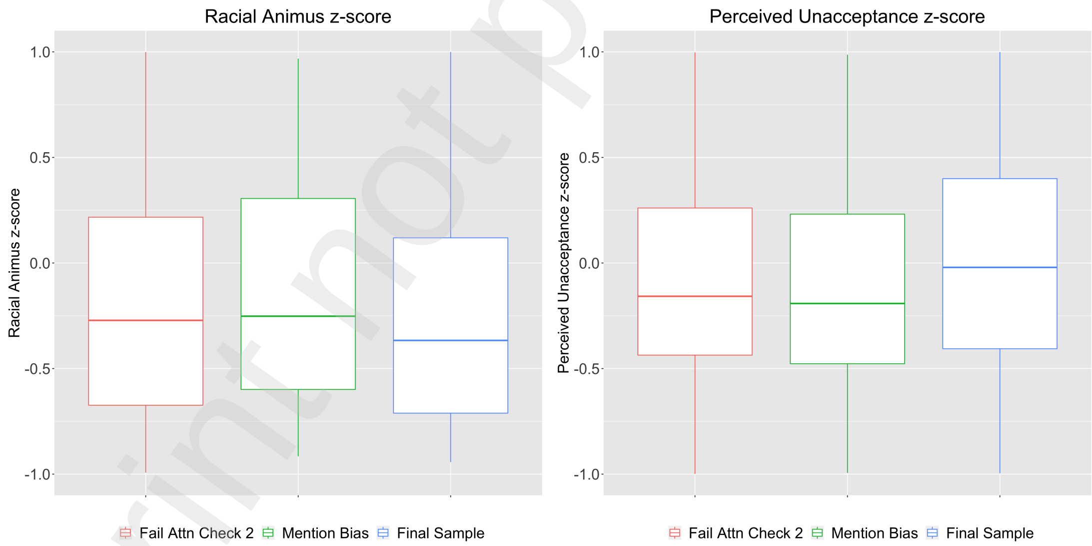


Figure D.2: Racial Animus and Perceived Unacceptance by Sample Selection

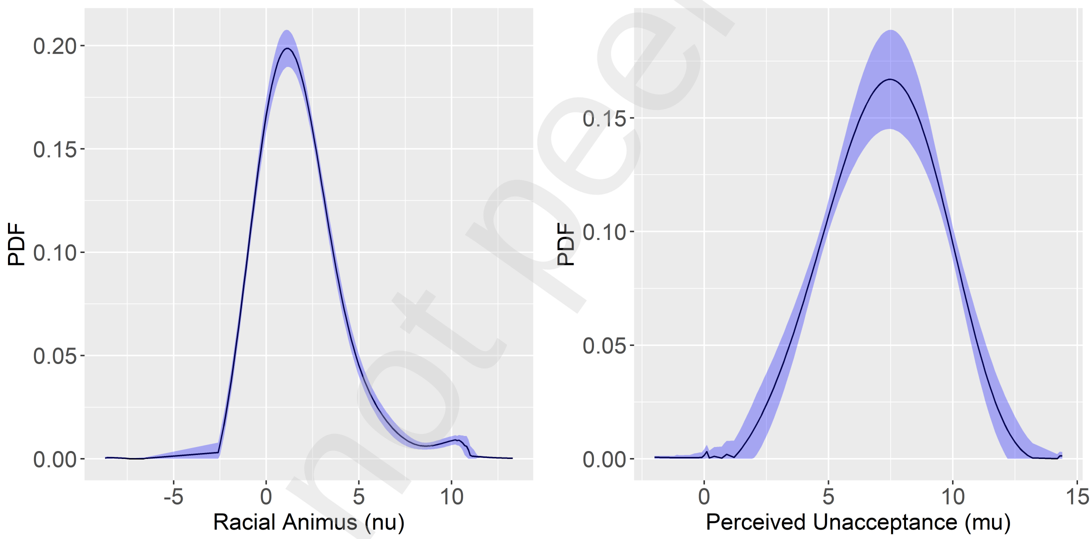


E Robustness Check by Including Sample Who Answered Our Survey Looked Biased

We repeated our analysis including small number of people who said our survey looked biased in either direction and confirmed most results remain qualitatively similar. One small difference was in the long run prediction of COVID (self) infection. Unlike our main results, COVID (self) infection turned out to increase two of xenophobic behaviors in the long run. This result is slightly different from our main results, which showed that the COVID (self) infection decreased all xenophobic behaviors in the long run. We conjecture this difference is due to the selection in this sample we described in Section D. This bias mention sample showed higher racial animus and lower perceived unacceptance than our final sample.

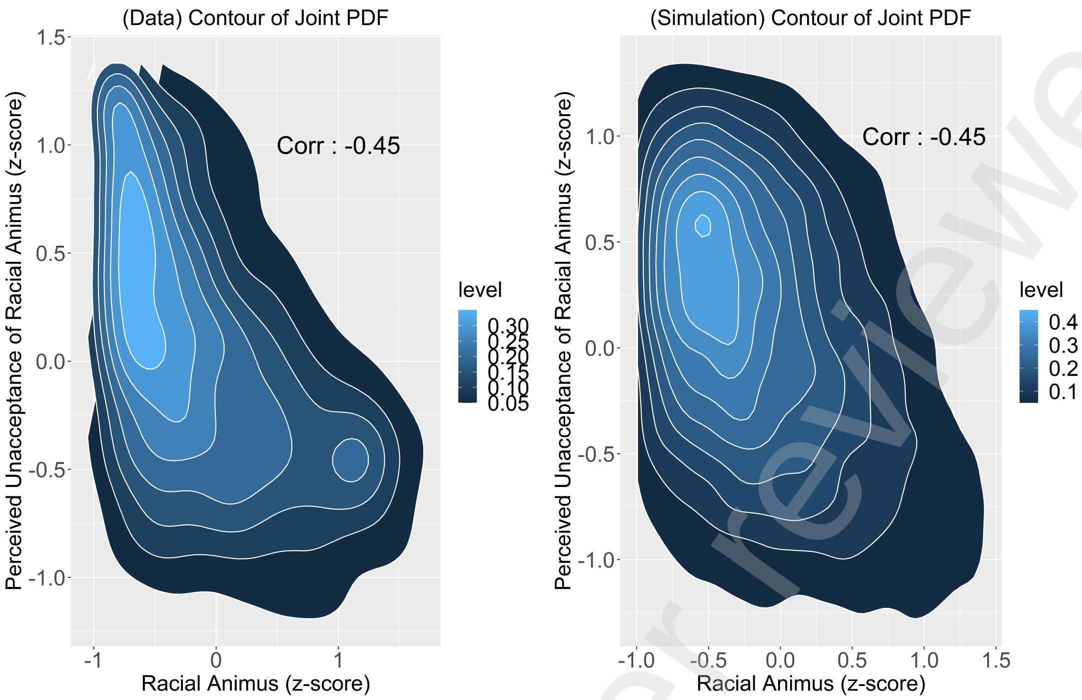
Below, we present the replication results.

Figure E.1: Replication of Figure 8 Including Sample Who Mentioned Bias



Note: This figure is the replication of 8 including sample who mentioned our survey looked biased either in favor of, or against Chinese immigrants. The figure shows the estimated densities of racial animus ν and perceived unacceptance μ using the Li and Vuong (1998) deconvolution kernel estimator. The 95% confidence interval is computed from bootstrapping 100 times and is denoted as a shaded area.

Figure E.2: Replication of Figure 9 Including Sample Who Mentioned Bias



Note: This figure is the replication of 9 including sample who mentioned our survey looked biased either in favor of, or against Chinese immigrants. This figure shows the model fit of the joint density of racial animus v and perceived unacceptance μ.

Table E.1: Replication of Table B.3 Including Sample Who Mentioned Bias

	α_0	α_1	$\sigma^2_{\epsilon^\nu_k}, \sigma^2_{\epsilon^\mu_g}$
acceptance	0	1	1.13
	(0)	(0)	(0.12)
warmth	0.9	0.95	1.74
	(0.06)	(0.03)	(0.14)
schoolRight	0.42	0.6	4.01
	(0.07)	(0.04)	(0.21)
healthHazard	1.59	0.71	6.79
	(0.08)	(0.04)	(0.25)
dislike	-0.26	0.84	2.85
	(0.05)	(0.03)	(0.19)
hatred	-0.28	0.69	2.91
	(0.05)	(0.03)	(0.19)
reduceChineseImm	0	1	5.03
	(0)	(0)	(0.44)
racistGoodRelation	-0.75	0.77	6.31
	(0.66)	(0.09)	(0.31)
ChinaVirusCriticism	1.23	0.69	7.33
	(0.7)	(0.1)	(0.34)
restrictRights	1.64	0.69	8.9
	(0.65)	(0.09)	(0.4)

Note: This Table is the replication of Table B.3 including sample who mentioned our survey looked biased either in favor of, or against Chinese immigrants. This table shows the estimates for measurement equation parameters in equation 7, 8. The anchor variables are 'acceptance' and 'reduceChineseImm', whose α_0 is normalized to 0 and α_1 is normalized to 1. The standard errors computed from bootstrapping the sample 100 times are in parenthesis.

Table E.2: Replication of Table 8 Including Sample Who Mention Bias

		Xenophobic action		
	Parameter Meaning	Xenophobic Donation	Xenophobic Petition	(DG) 1(White>Chinese)
κ	relative importance of image concern	2.14	0.62	0.22
		(0.29)	(0.06)	(0.08)
c	location parameter for μ	-8.04	0.43	3.48
		(1.38)	(0.25)	(0.26)
β	Gumbel shock scale	8.77	4.35	3.70
		(1.08)	(0.24)	(0.25)
θ	Joe copula parameter		2.08	
			(0.09)	

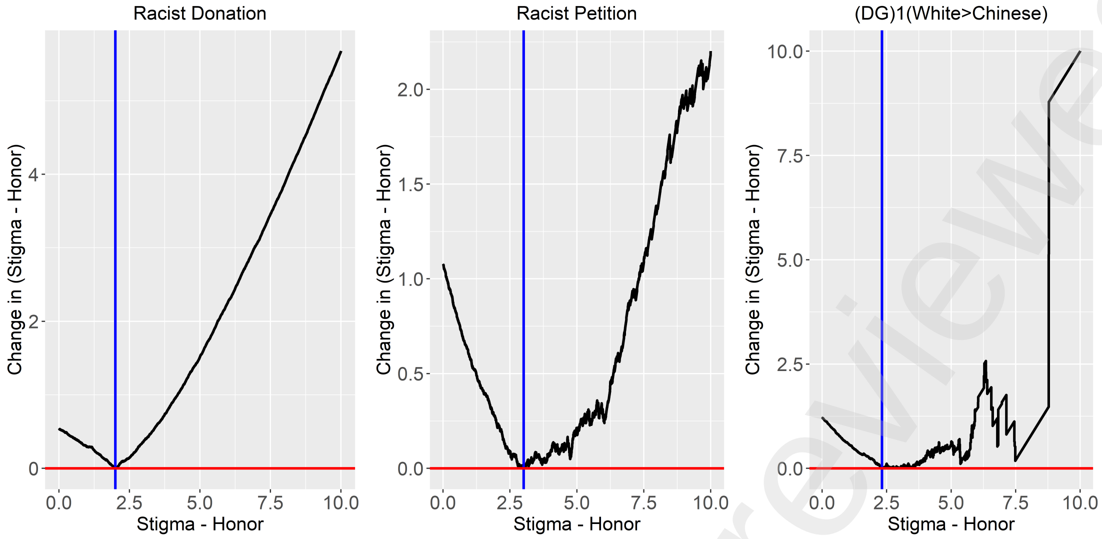
Note : This Table is the replication of Table 8 including sample who mentioned our survey looked biased either in favor of, or against Chinese immigrants. The standard errors are in parenthesis. They are computed from bootstrapping the entire estimation procedure 100 times.

Table E.3: Replication of Table 9 Including Sample Who Mention Bias

	Xenophobic Donation		Xenophobic Petition		(DG)1(White>Chinese)	
Moments	Data	Model	Data	Model	Data	Model
ξ_0	0.24	0.25	0.10	0.10	0.09	0.09
	[0.23,0.26]		[0.09,0.11]		[0.08,0.10]	
ξ_1	0.11	0.13	0.12	0.11	0.08	0.09
	[0.09,0.14]		[0.10,0.14]		[0.06,0.10]	
ξ_2	-0.17	-0.16	-0.05	-0.06	-0.03	-0.02
	[-0.19,-0.15]		[-0.07,-0.03]		[-0.04,-0.01]	
$P(a=1)$	0.25	0.25	0.10	0.10	0.09	0.09
	[0.23,0.26]		[0.09,0.11]		[0.08,0.10]	
$E\widehat{[v\|a=1]} - E\widehat{[v\|a=0]}$	1.98	2.00	3.25	3.01	2.38	2.32
	[1.77,2.20]		[2.93,3.57]		[2.00,2.76]	

Note : This Table is the replication of Table 9 including sample who mentioned our survey looked biased either in favor of, or against Chinese immigrants. 95% CIs of data moments are in brackets.

Figure E.3: Replication of Figure 10 Including Sample Who Mention Bias



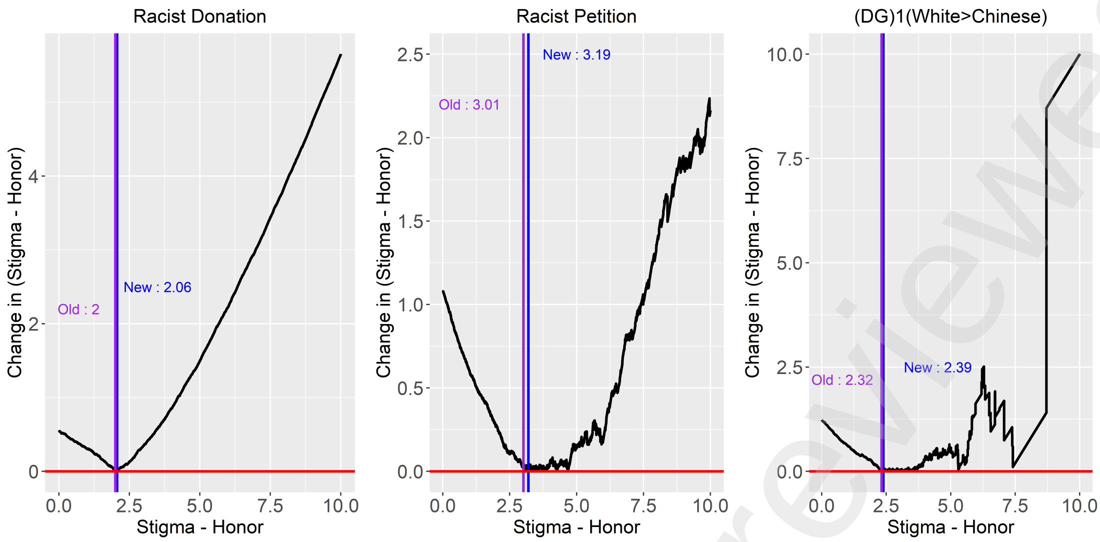
Note: This figure shows that there are multiple equilibria under the structural parameter estimates (for xenophobic behavior during the dictator game, titled '(DG)1(White>Chinese)'). There is no other equilibrium for xenophobic donation and xenophobic petition.

Table E.4: Replication of Table 11 Including Sample Who Mention Bias

		shifts racial animus (ν) by 0.13 SD		shifts perceived unacceptance (μ) by 0.13 SD	
		Holding the (stigma - honor) fixed as baseline			
	baseline	p.p. ch	% ch	p.p. ch	% ch
Xenophobic Donation	0.25	-0.50	-2.04	-2.10	-8.57
Xenophobic Petition	0.10	-0.49	-5.15	-0.84	-8.84
Xenophobic Dictator Game	0.09	-0.53	-5.87	-0.28	-3.10
		Updating the (stigma - honor) in new equilibrium			
	baseline	p.p. ch	% ch	p.p. ch	% ch
Xenophobic Donation	0.25	-1.06	-4.31	-4.05	-16.53
Xenophobic Petition	0.10	-1.46	-15.30	-4.82	-50.42
Xenophobic Dictator Game	0.09	-1.15	-12.71	-1.00	-11.08

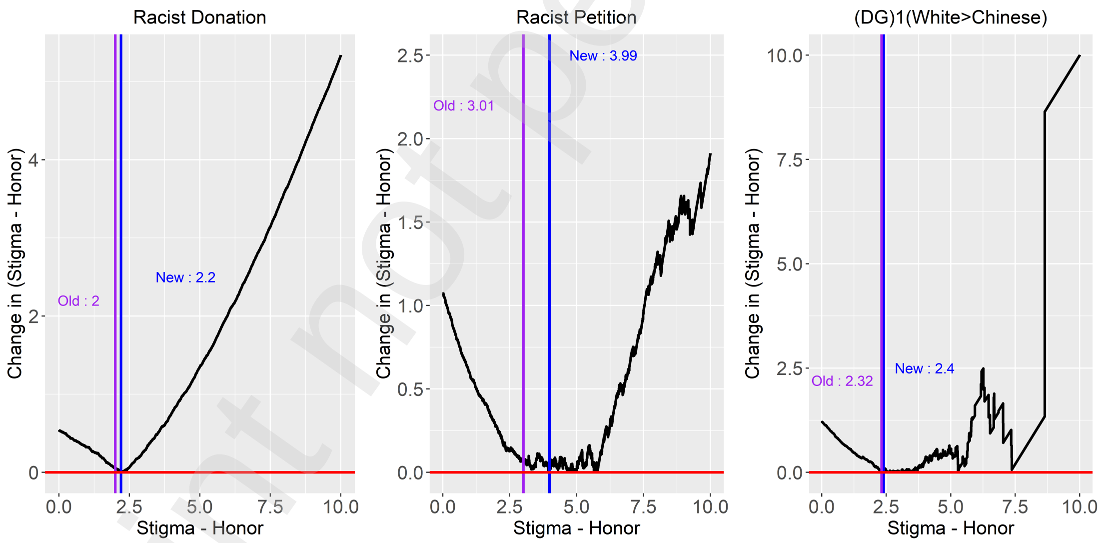
Note: This Table is the replication of Table 9 including sample who mentioned our survey looked biased either in favor of, or against Chinese immigrants. This table shows the counterfactual predictions for shifting the racial animus ν and perceived unacceptance μ by 0.13 standard deviations. The 0.13 standard deviation is the difference between an average White person and average non-White, non-Black, non-Asian person (Others) (Figure 7). The top panel shows a short-run prediction holding the reputational gain fixed at the baseline level and the bottom panel shows a long run prediction when updating the reputational gain to a new level.

Figure E.4: Replication of Figure B.4 Including Sample Who Mention Bias



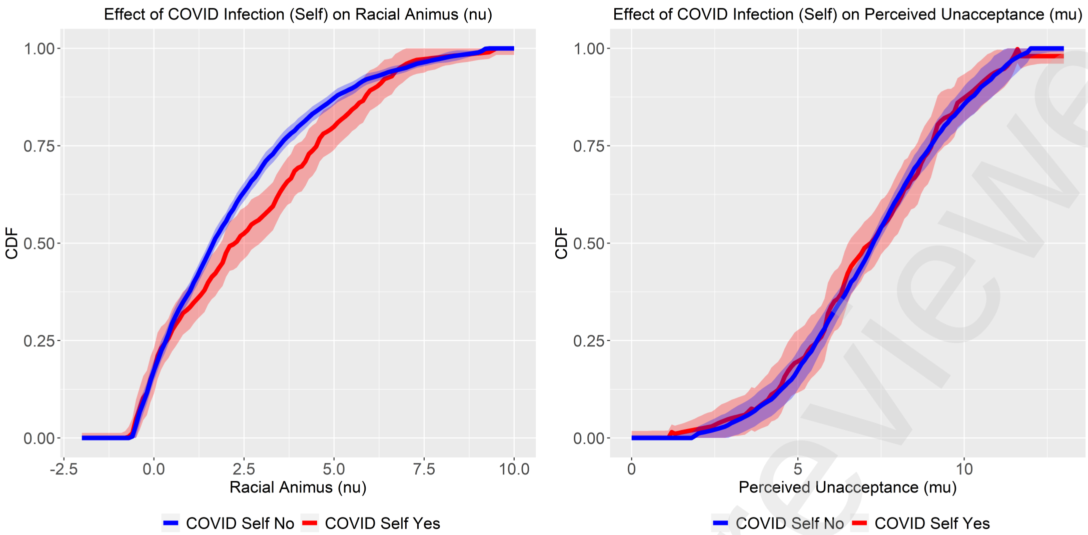
Note: This figure shows that there are multiple equilibria in counterfactual 7.1shifting ν by 0.13 standard deviation (for xenophobic petition and xenophobic behavior during the dictator game, titled '(DG)1(White>Chinese)'). We choose the equilibrium whose reputational gain is closest to the baseline level following our equilibrium selection rule. There is no other equilibrium for xenophobic donation.

Figure E.5: Replication of Figure B.5 Including Sample Who Mention Bias



Note: This figure shows that there are multiple equilibria in counterfactual 7.1 shifting μ by 0.13 standard deviation (for xenophobic petition and xenophobic behavior during the dictator game, titled '(DG)1(White>Chinese)'). We choose the equilibrium whose reputational gain is closest to the baseline level following our equilibrium selection rule. There is no other equilibrium for xenophobic donation.

Figure E.6: Replication of Figure 11 Including Sample Who Mention Bias



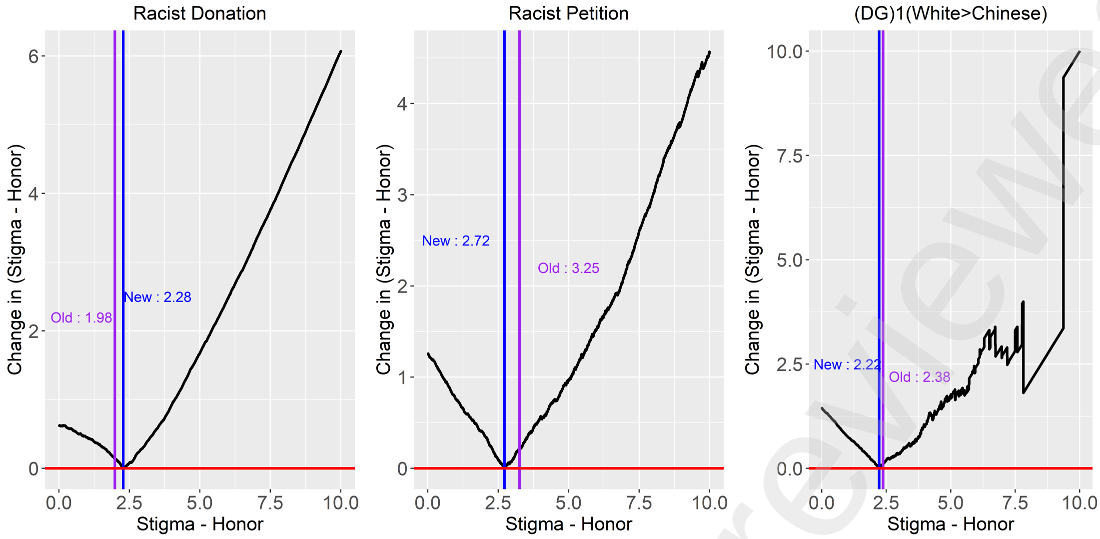
Note: This figure shows the prediction on the CDF of racial animus ν and perceived unacceptance μ if everyone gets infected of COVID (COVID Self Yes) and if everyone does not get infected of COVID (COVID Self No). The COVID infection polarizes racial animus as shown by more mass at both tails for COVID Self Yes. On the other hand, COVID infection does not change the distribution of perceived unacceptance.

Table E.5: Replication of Table 12 Including Sample Who Mention Bias

	Holding the (stigma - honor) fixed as baseline			
	COVID (Self) Infection		Yes - No	
	No	Yes	p.p. ch	% ch
Xenophobic Donation	0.26	0.27	1.62	6.30
Xenophobic Petition	0.09	0.10	1.40	15.46
Xenophobic Dictator Game	0.09	0.10	1.35	14.84
	Updating the (stigma - honor) in new eqm			
	No	Yes	p.p. ch	% ch
Xenophobic Donation	0.25	0.25	-0.07	-0.29
Xenophobic Petition	0.13	0.14	1.20	9.43
Xenophobic Dictator Game	0.11	0.12	0.51	4.44

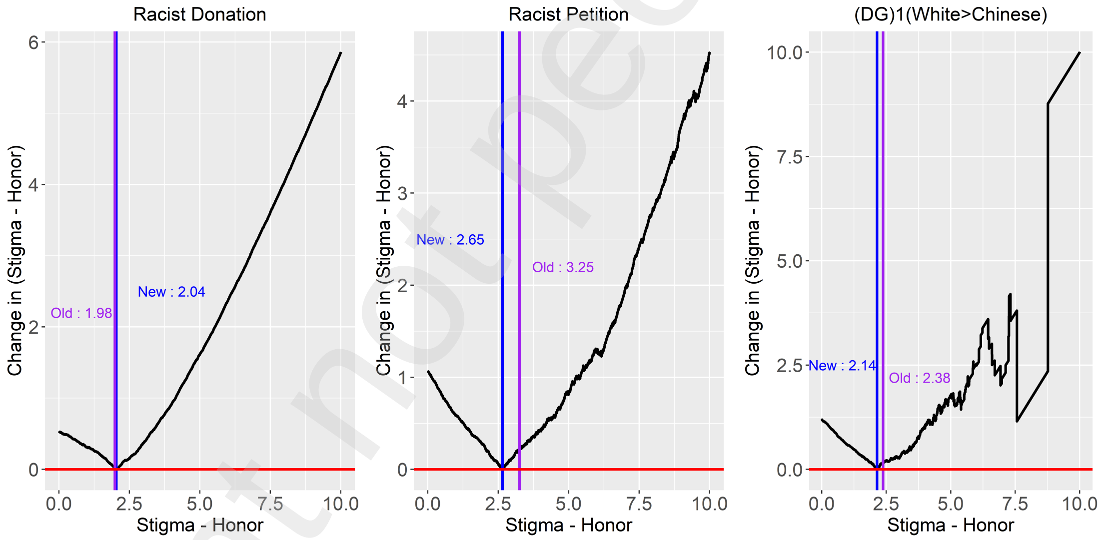
Note: This Table is the replication of Table 9 including sample who mentioned our survey looked biased either in favor of, or against Chinese immigrants. This table shows the counterfactual predictions for when everyone gets infected with COVID and when no one gets infected with COVID. The top panel shows a short-run prediction holding the reputational gain fixed at the baseline level and the bottom panel shows a long-run prediction when updating the reputational gain to a new level.

Figure E.7: Replication of Figure B.6 Including Sample Who Mention Bias



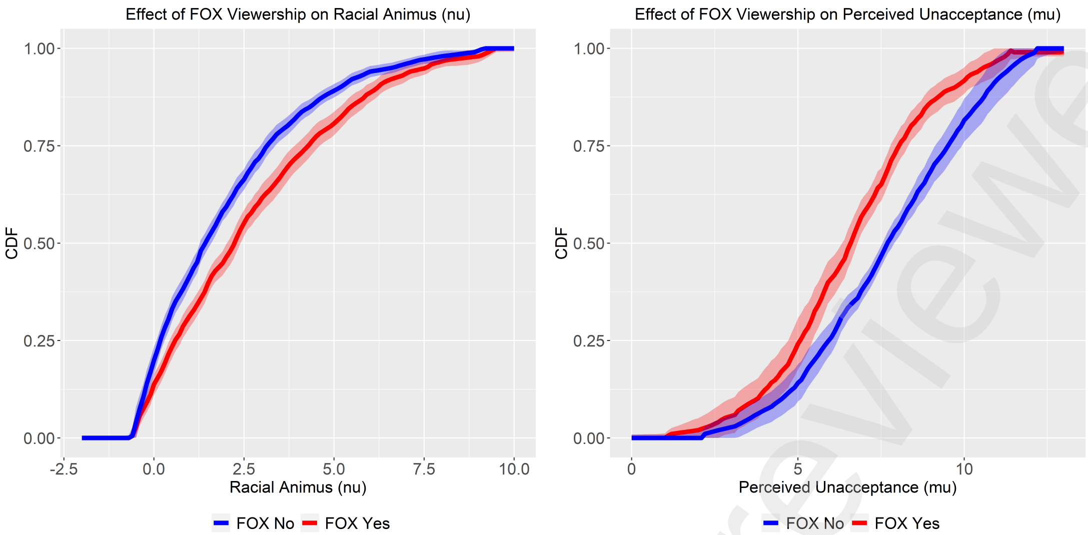
Note: This figure shows that there are no other equilibria in counterfactual 7.2 for when everyone gets infected with COVID.

Figure E.8: Replication of Figure B.7 Including Sample Who Mention Bias



Note: This figure shows that there are no other equilibria in counterfactual 7.2 for when no one gets infected with COVID.

Figure E.9: Replication of Figure 12 Including Sample Who Mention Bias



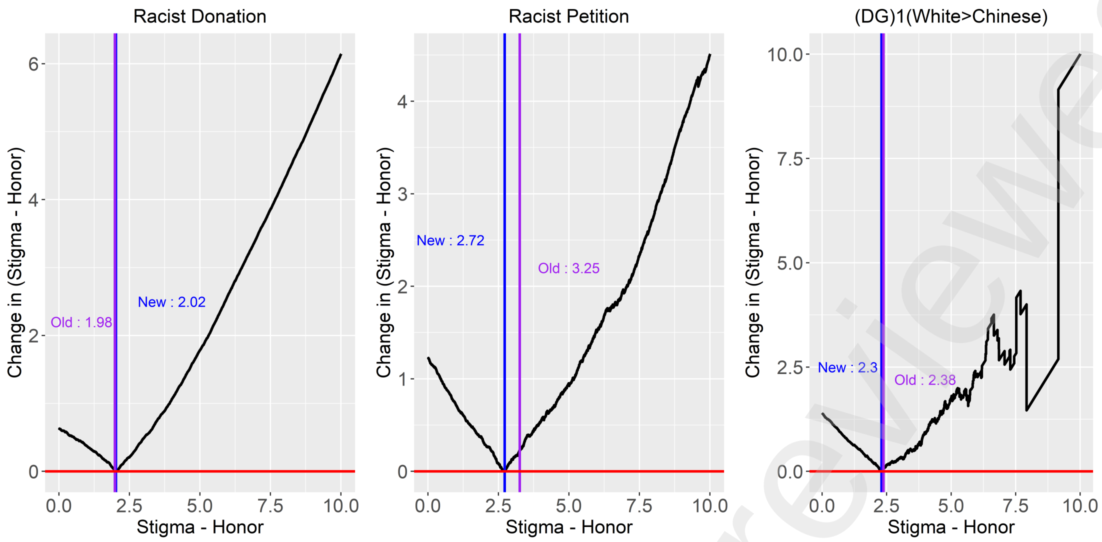
Note: This figure shows the counterfactual predictions for when everyone watches Fox News versus when everyone does not watch Fox News. Fox News increases racial animus and decreases perceived unacceptance at every percentile.

Table E.6: Replication of Table 13 Including Sample Who Mention Bias

	Holding the (stigma - honor) fixed as baseline			
	FOX Viewership		Yes - No	
	No	Yes	p.p. ch	% ch
Xenophobic Donation	0.23	0.31	7.88	34.46
Xenophobic Petition	0.08	0.12	4.19	54.81
Xenophobic Dictator Game	0.08	0.11	2.67	32.30
	Updating the (stigma - honor) in new eqm			
	No	Yes	p.p. ch	% ch
Xenophobic Donation	0.23	0.30	7.92	35.19
Xenophobic Petition	0.12	0.15	3.90	33.71
Xenophobic Dictator Game	0.12	0.12	0.04	0.38

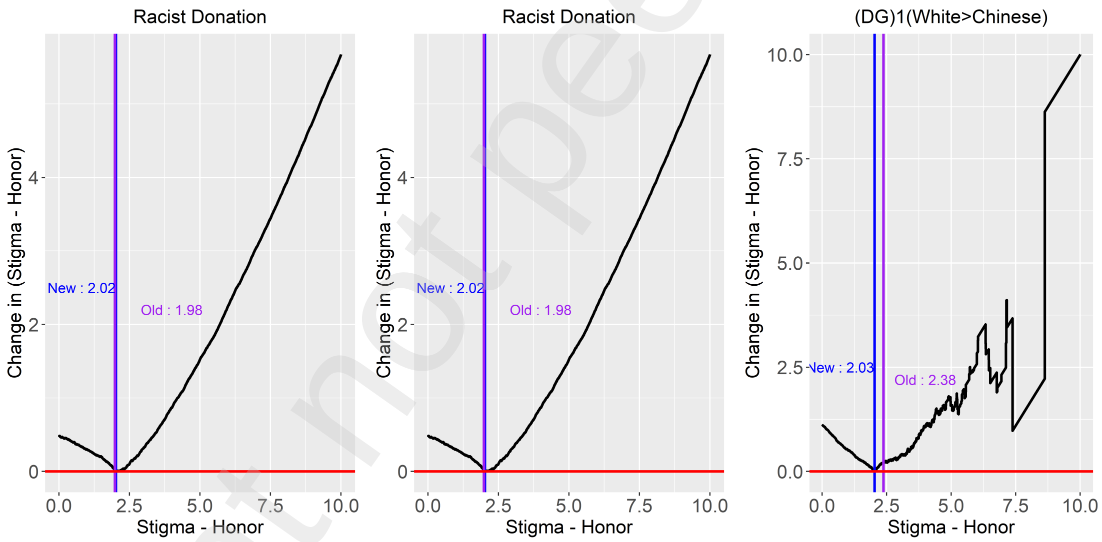
Note: This Table is the replication of Table 9 including sample who mentioned our survey looked biased either in favor of, or against Chinese immigrants. This table shows the counterfactual prediction for when everyone watches Fox News and for when no one watches Fox News. The top panel shows a short-run prediction holding the reputational gain fixed at the baseline level and the bottom panel shows a long-run prediction when updating the reputational gain to a new level.

Figure E.10: Replication of Figure B.8 Including Sample Who Mention Bias



Note: This figure shows that there are no other equilibria in counterfactual 7.3 for when everyone watches Fox News.

Figure E.11: Replication of Figure B.9 Including Sample Who Mention Bias



Note: This figure shows that there are no other equilibria in counterfactual 7.3 for when no one watches Fox News.

F Robustness Check with Different Anchor Proxy Variables

We estimated the densities of racial animus and perceived unacceptance using different proxy variables to anchor the location and scale. We found the density shapes are qualitatively invariant: the racial animus distribution is skewed to the right and the perceived unacceptance distribution is symmetric and inverted u-shaped. The location and the dispersion of each density is different and this means the structural parameter estimates must change to adjust for different location and scale of latent variables. However, the model implication can be invariant after the structural parameters are adjusted for the new location and scale.

We provide robustness result when we use one other pair of different anchor proxy variables. We have 6 proxy variables for racial animus and 4 proxy variables for perceived unacceptance. So we have 23 pairs of anchor proxy variables which are different from our baseline choice. Checking all 23 cases is infeasible, so we choose one proxy variable each which gives the most different density estimate from when we use the baseline anchor proxy variables. They are 'schoolRight' and 'racistGoodRelation' (Figure F.1).

We confirmed that most results are qualitatively similar. Below we present the replicated results using 'schoolRight' and 'racistGoodRelation' as anchor proxies. The two small differences we found are in the long run prediction of COVID (self) infection and Fox News viewership for one xenophobic behavior each. COVID (self) infection turned out to increase xenophobic petition in the long run, contrary to our main result which showed COVID (self) infection decreases every xenophobic behavior in the long run. Fox News viewership in this case increases every xenophobic behavior in the long run, but in our main result, Fox News marginally decreases one xenophobic behavior (dictator game) in the long run. However, we consider this difference is rather minor and overall, most results are qualitatively similar.

Figure F.1: Changing the Anchor Proxy Variables

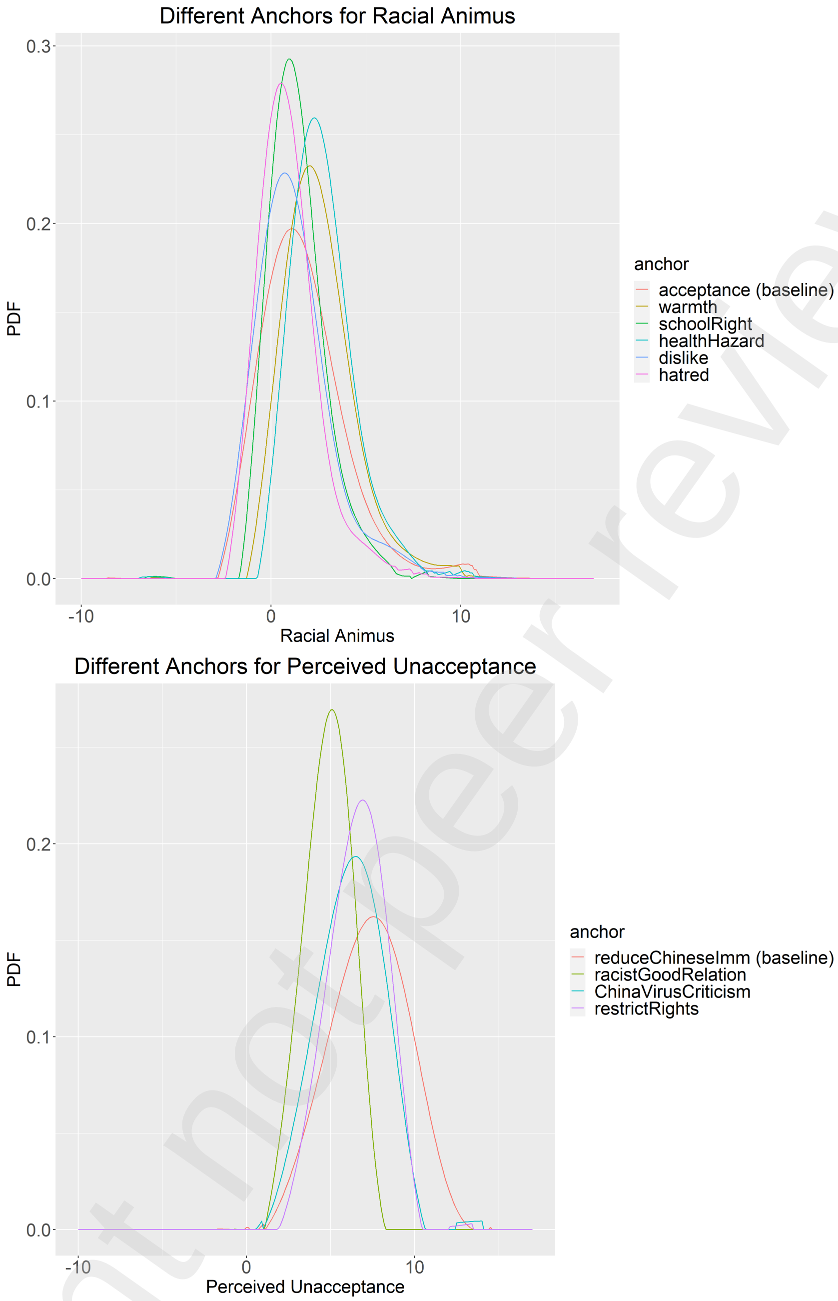
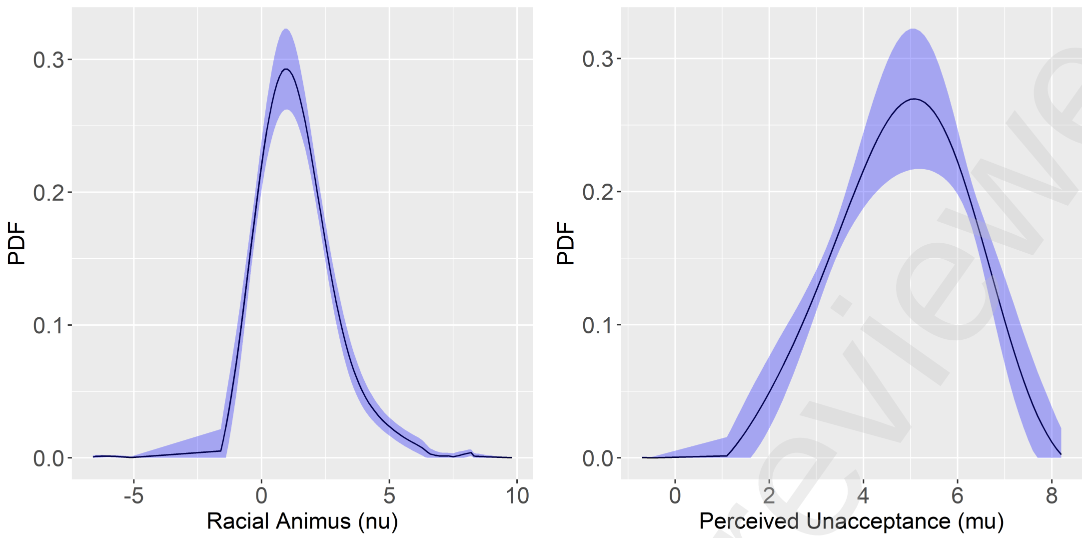
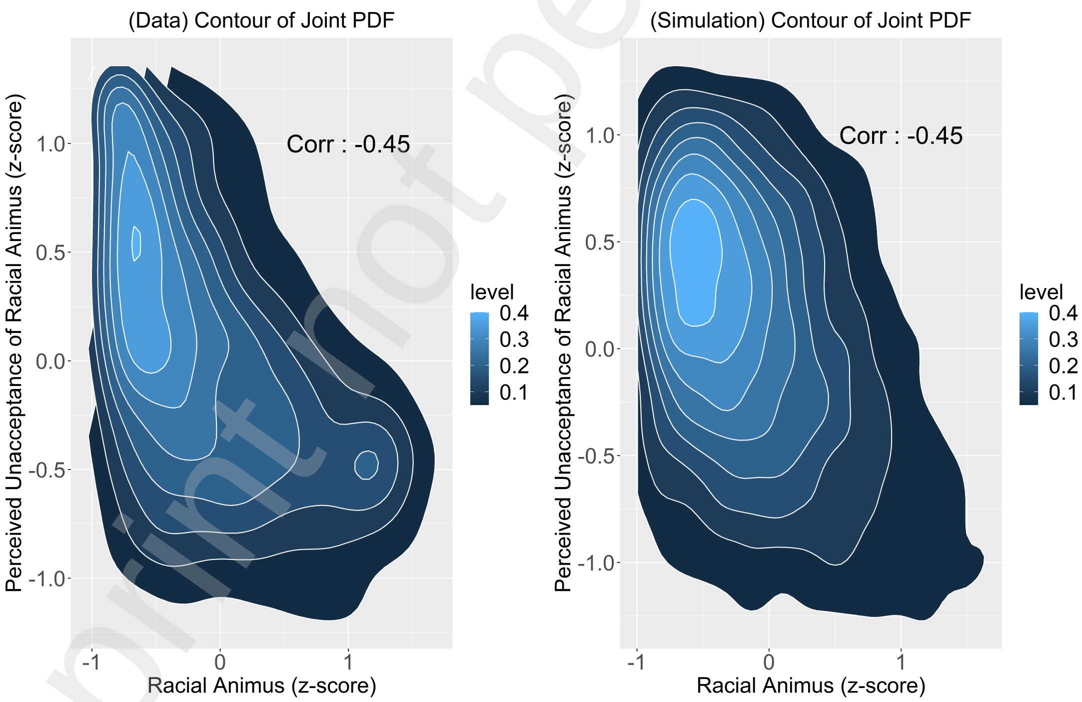


Figure F.2: Replication of Figure 8 When Using Different Anchor Proxy Variables



Note: This figure is the replication of 8 when using different anchor proxy variables. The new anchor variables are 'schoolRight' and 'racistGoodRelation'. The figure shows the estimated densities of racial animus ν and perceived unacceptance μ using the Li and Vuong (1998) deconvolution kernel estimator. The 95% confidence interval is computed from bootstrapping 100 times and is denoted as a shaded area.

Figure F.3: Replication of Figure 9 When Using Different Anchor Proxy Variables



Note: This figure is the replication of 9 when using different anchor proxy variables. The new anchor variables are 'schoolRight' and 'racistGoodRelation'. This figure shows the model fit of the joint density of racial animus ν and perceived unacceptance μ.

Table F.1: Replication of Table B.3 Using Different Anchor Proxy Variables

	α_0	α_1	$\sigma^2_{\epsilon^\nu_k}, \sigma^2_{\epsilon^\mu_g}$
acceptance	-0.15	1.37	2.02
	(0.12)	(0.08)	(0.25)
warmth	0.99	1.15	3.21
	(0.12)	(0.08)	(0.26)
schoolRight	0	1	3.51
	(0)	(0)	(0.23)
healthHazard	0.35	1.62	3.56
	(0.18)	(0.11)	(0.44)
dislike	-0.28	1.09	3.62
	(0.11)	(0.07)	(0.29)
hatred	-0.29	0.89	3.37
	(0.09)	(0.07)	(0.24)
reduceChineseImm	-1.98	1.9	3.41
	(1.48)	(0.3)	(0.79)
racistGoodRelation	0	1	6.89
	(0)	(0)	(0.27)
ChinaVirusCriticism	0.13	1.25	6.79
	(1.02)	(0.21)	(0.51)
restrictRights	1.83	0.98	9.34
	(0.72)	(0.14)	(0.42)

Note: This Table is the replication of Table B.3 when using different anchor proxy variables. The new anchor variables are 'schoolRight' and 'racistGoodRelation', whose α_0 is normalized to 0 and α_1 is normalized to 1. This table shows the estimates for measurement equation parameters in equation 7, 8. The standard errors computed from bootstrapping the sample 100 times are in parenthesis.

Table F.2: Replication of Table 8 Using Different Anchor Proxy Variables

	Parameter Meaning	Xenophobic action Xenophobic Donation	 Xenophobic Petition	 (DG) 1(White>Chinese)
κ	relative importance of image concern	3.29	0.79	0.75
		(1.18)	(0.10)	(0.15)
c	location parameter for μ	-8.20	0.28	4.27
		(3.68)	(0.36)	(0.19)
β	Gumbel shock scale	5.69	2.34	3.42
		(1.58)	(0.15)	(0.20)
θ	Joe copula parameter		2.05	
			(0.10)	

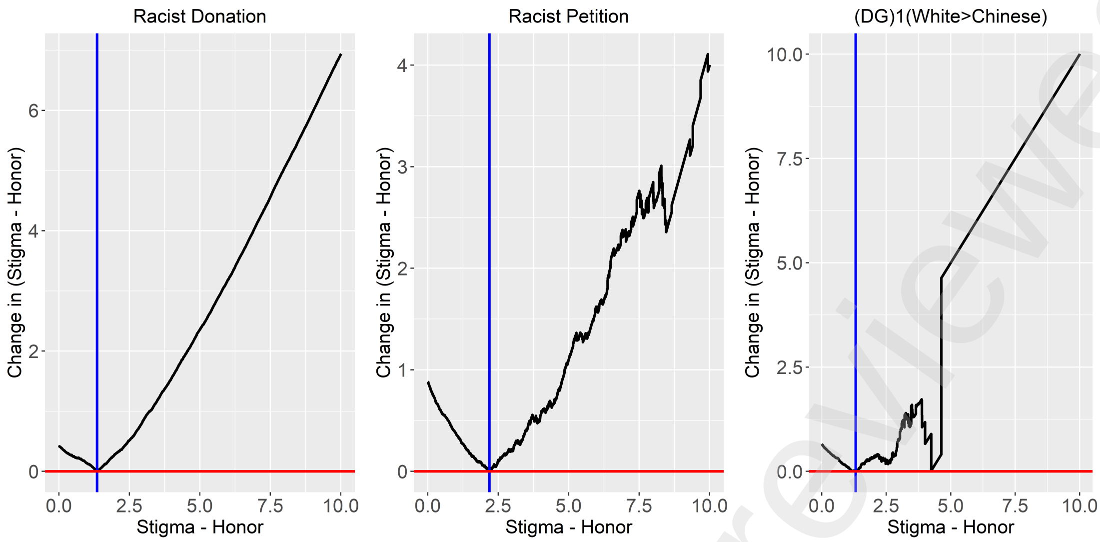
Note : This Table is the replication of Table 8 when using different anchor proxy variables. The new anchor variables are 'schoolRight' and 'racistGoodRelation'. The standard errors are in parenthesis. They are computed from bootstrapping the entire estimation procedure 100 times.

Table F.3: Replication of Table 9 When Using Different Anchor Proxy Variables

	Xenophobic Donation		Xenophobic Petition		(DG)1(White>Chinese)	
Moments	Data	Model	Data	Model	Data	Model
ξ_0	0.23	0.23	0.09	0.09	0.09	0.09
	[0.21,0.24]		[0.08,0.10]		[0.07,0.10]	
ξ_1	0.11	0.12	0.12	0.12	0.08	0.07
	[0.09,0.13]		[0.09,0.14]		[0.06,0.10]	
ξ_2	-0.17	-0.16	-0.05	-0.07	-0.03	-0.04
	[-0.19,-0.14]		[-0.07,-0.03]		[-0.05,-0.01]	
$P(a=1)$	0.23	0.23	0.09	0.09	0.09	0.09
	[0.21,0.25]		[0.08,0.10]		[0.08,0.10]	
$\widehat{E[v\|a=1]} - \widehat{E[v\|a=0]}$	1.36	1.36	2.31	2.19	1.71	1.31
	[1.13,1.59]		[1.91,2.72]		[1.29,2.12]	

Note : This Table is the replication of Table 9 when using different anchor proxy variables. The new anchor variables are 'schoolRight' and 'racistGoodRelation'. 95% CIs of data moments are in brackets.

Figure F.4: Replication of Figure 10 When Using Different Anchor Proxy Variables



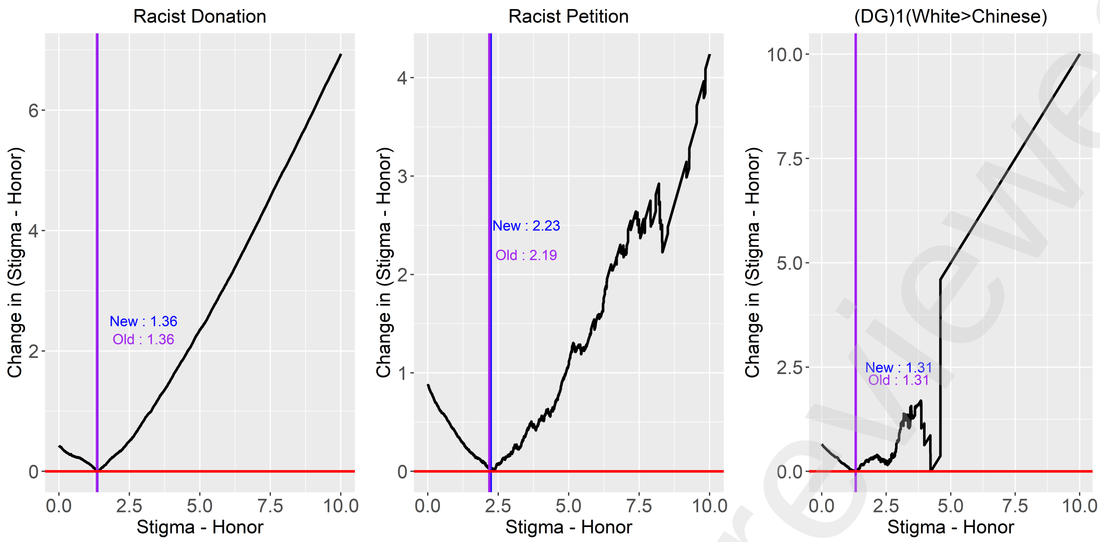
Note: This figure shows that there are multiple equilibria under the structural parameter estimates (for xenophobic behavior during the dictator game, titled '(DG)1(White>Chinese)'). There is no other equilibrium for xenophobic donation and xenophobic petition.

Table F.4: Replication of Table 11 When Using Different Anchor Proxy Variables

		shifts racial animus (ν) by 0.13 SD		shifts perceived unacceptance (μ) by 0.13 SD	
		Holding the (stigma - honor) fixed as baseline			
	baseline	p.p. ch	% ch	p.p. ch	% ch
Xenophobic Donation	0.23	-0.47	-2.10	-1.93	-8.55
Xenophobic Petition	0.09	-0.47	-5.29	-0.70	-7.98
Xenophobic Dictator Game	0.09	-0.41	-4.63	-0.38	-4.34
		Updating the (stigma - honor) in new equilibrium			
	baseline	p.p. ch	% ch	p.p. ch	% ch
Xenophobic Donation	0.23	-0.52	-2.29	-2.79	-12.38
Xenophobic Petition	0.09	-0.73	-8.27	-1.57	-17.88
Xenophobic Dictator Game	0.09	-0.41	-4.73	-0.41	-4.63

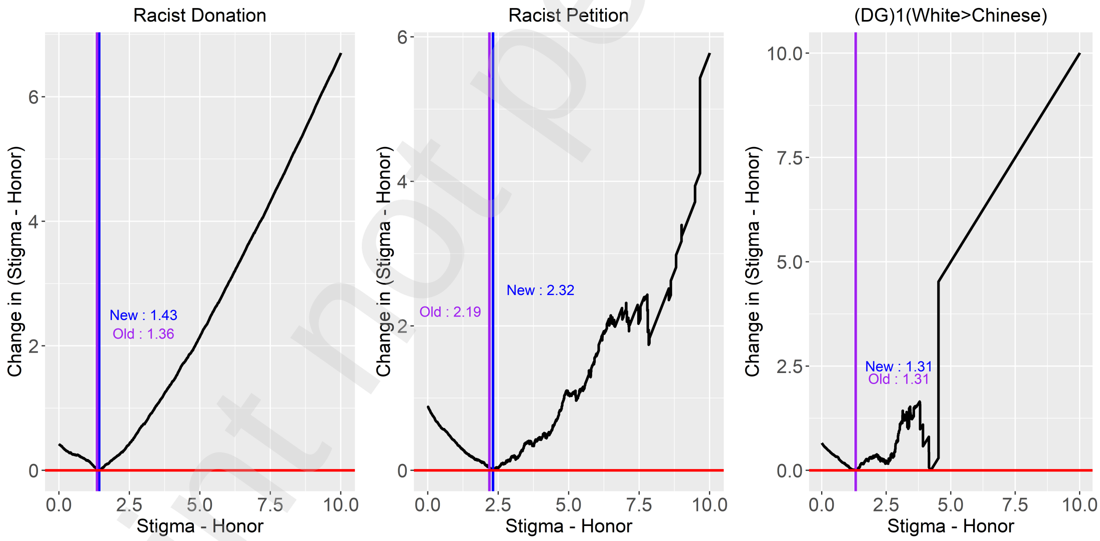
Note: This Table is the replication of Table 11 when using different anchor proxy variables. The new anchor variables are 'schoolRight' and 'racistGoodRelation'. This table shows the counterfactual predictions for shifting the racial animus ν and perceived unacceptance μ by 0.13 standard deviations. The 0.13 standard deviation is the difference between an average White person and average non-White, non-Black, non-Asian person (Others) (Figure 7). The top panel shows a short-run prediction holding the reputational gain fixed at the baseline level and the bottom panel shows a long run prediction when updating the reputational gain to a new level.

Figure F.5: Replication of Figure B.4 When Using Different Anchor Proxy Variables



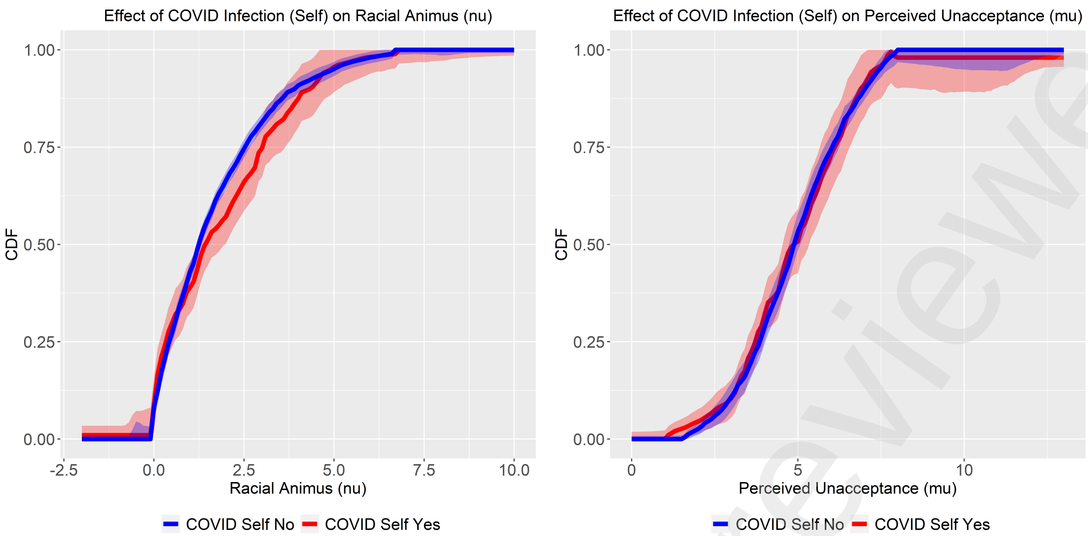
Note: This figure shows that there are multiple equilibria in counterfactual 7.1 shifting ν by 0.13 standard deviation (for xenophobic behavior during the dictator game, titled '(DG)1(White>Chinese)'). We choose the equilibrium whose reputational gain is closest to the baseline level following our equilibrium selection rule. There is no other equilibrium for xenophobic donation and xenophobic petition.

Figure F.6: Replication of Figure B.5 When Using Different Anchor Proxy Variables



Note: This figure shows that there are multiple equilibria in counterfactual 7.1shifting μ by 0.13 standard deviation (for xenophobic behavior during the dictator game, titled '(DG)1(White>Chinese)'). We choose the equilibrium whose reputational gain is closest to the baseline level following our equilibrium selection rule. There is no other equilibrium for xenophobic donation and xenophobic petition.

Figure F.7: Replication of Figure 11 When Using Different Anchor Proxy Variables



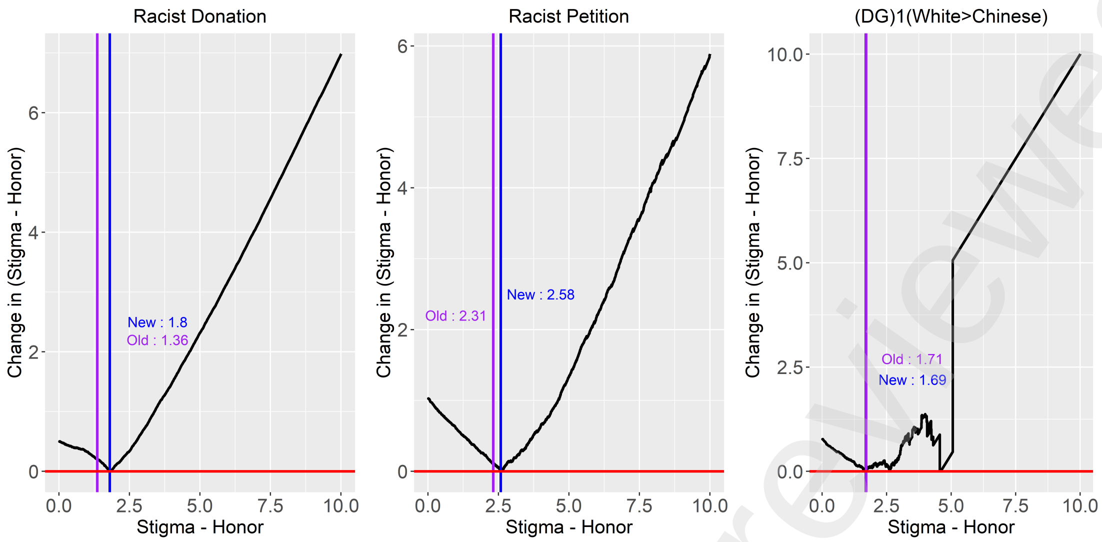
Note: This figure shows the prediction on the CDF of racial animus ν and perceived unacceptance μ if everyone gets infected of COVID (COVID Self Yes) and if everyone does not get infected of COVID (COVID Self No). The COVID infection polarizes racial animus as shown by more mass at both tails for COVID Self Yes. On the other hand, COVID infection does not change the distribution of perceived unacceptance.

Table F.5: Replication of Table 12 When Using Different Anchor Proxy Variables

	Holding the (stigma - honor) fixed as baseline			
	COVID (Self) Infection		Yes - No	
	No	Yes	p.p. ch	% ch
Xenophobic Donation	0.23	0.25	1.36	5.81
Xenophobic Petition	0.09	0.10	1.29	14.35
Xenophobic Dictator Game	0.05	0.05	0.46	9.68
	Updating the (stigma - honor) in new eqm			
	No	Yes	p.p. ch	% ch
Xenophobic Donation	0.21	0.21	-0.07	-0.33
Xenophobic Petition	0.07	0.08	1.15	15.80
Xenophobic Dictator Game	0.06	0.05	-1.01	-15.95

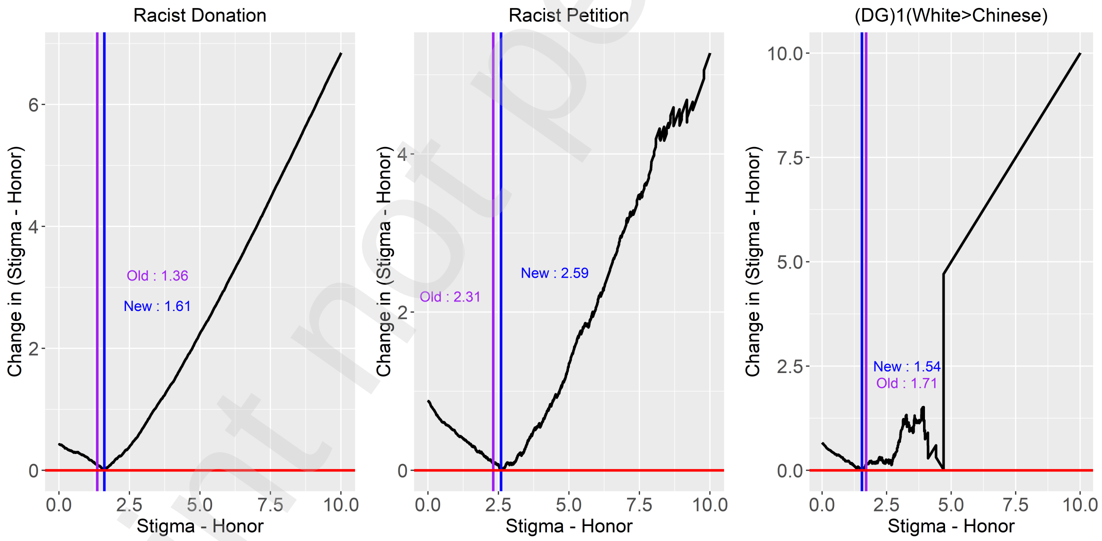
Note: This Table is the replication of Table 12 when using different anchor proxy variables. The new anchor variables are 'schoolRight' and 'racistGoodRelation'. This table shows the counterfactual predictions for when everyone gets infected with COVID and when no one gets infected with COVID. The top panel shows a short-run prediction holding the reputational gain fixed at the baseline level and the bottom panel shows a long-run prediction when updating the reputational gain to a new level.

Figure F.8: Replication of Figure B.6 When Using Different Anchor Proxy Variables



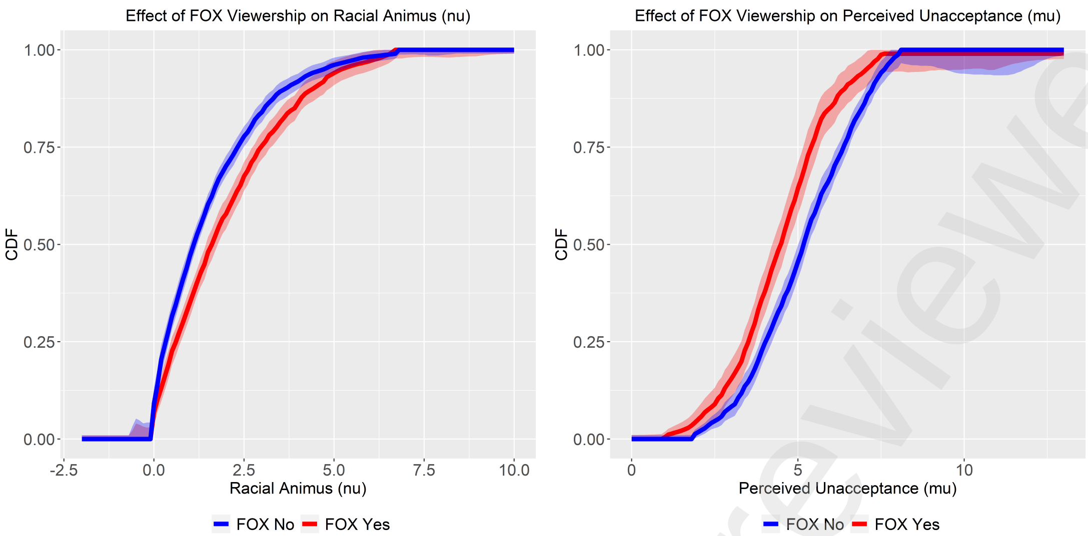
Note: This figure shows that there are multiple equilibria in counterfactual 7.2 for everyone gets infected with COVID (for xenophobic behavior during the dictator game, titled '(DG)1(White>Chinese)')). We choose the equilibrium whose reputational gain is closest to the baseline level following our equilibrium selection rule. There is no other equilibrium for xenophobic donation and xenophobic petition.

Figure F.9: Replication of Figure B.7 When Using Different Anchor Proxy Variables



Note: This figure shows that there are multiple equilibria in counterfactual 7.2 for no one gets infected with COVID (for xenophobic behavior during the dictator game, titled '(DG)1(White>Chinese)')). We choose the equilibrium whose reputational gain is closest to the baseline level following our equilibrium selection rule. There is no other equilibrium for xenophobic donation and xenophobic petition.

Figure F.10: Replication of Figure 12 When Using Different Anchor Proxy Variables



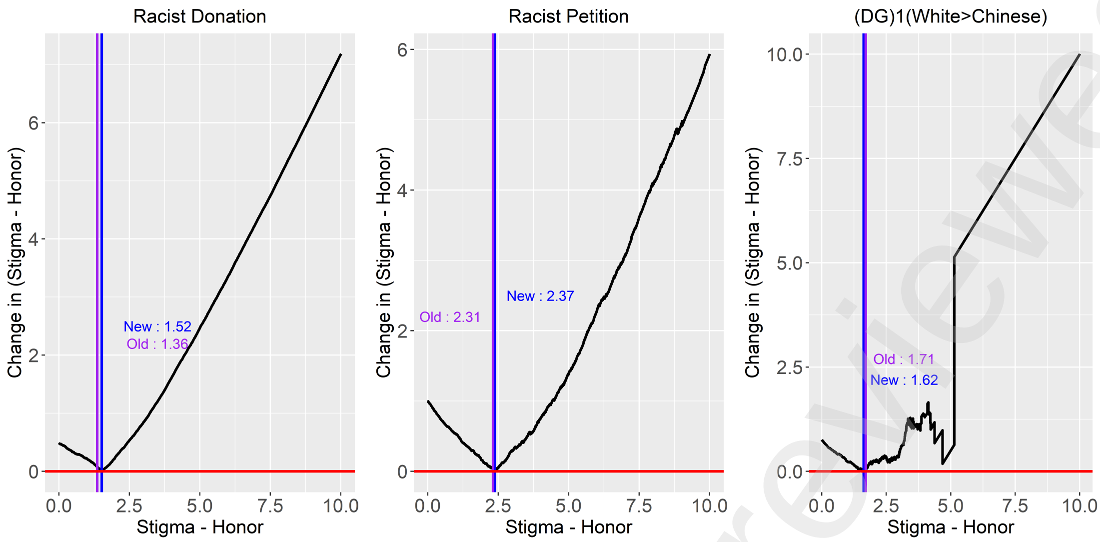
Note: This figure shows the counterfactual predictions for when everyone watches Fox News versus when everyone does not watch Fox News. Fox News increases racial animus and decreases perceived unacceptance at every percentile.

Table F.6: Replication of Table 13 When Using Different Anchor Proxy Variables

	Holding the (stigma - honor) fixed as baseline			
	FOX Viewership		Yes - No	
	No	Yes	p.p. ch	% ch
Xenophobic Donation	0.21	0.29	8.20	39.81
Xenophobic Petition	0.08	0.12	4.46	58.75
Xenophobic Dictator Game	0.04	0.06	1.67	39.40
	Updating the (stigma - honor) in new eqm			
	No	Yes	p.p. ch	% ch
Xenophobic Donation	0.18	0.27	9.37	53.53
Xenophobic Petition	0.04	0.11	7.01	156.52
Xenophobic Dictator Game	0.06	0.07	1.22	22.09

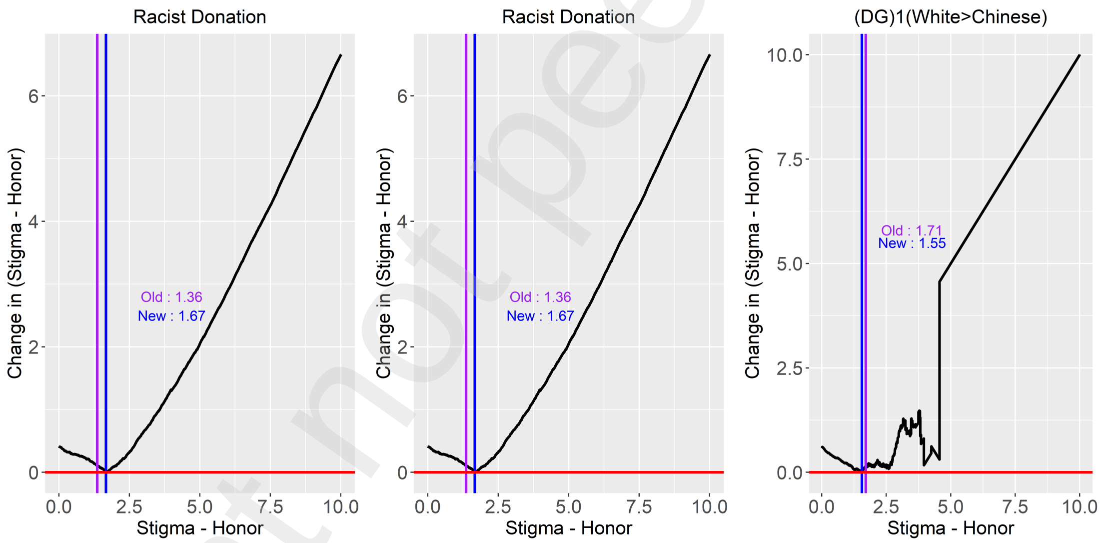
Note: This Table is the replication of Table 13 when using different anchor proxy variables. The new anchor variables are 'schoolRight' and 'racistGoodRelation'. This table shows the counterfactual prediction for when everyone watches Fox News and for when no one watches Fox News. The top panel shows a short-run prediction holding the reputational gain fixed at the baseline level and the bottom panel shows a long-run prediction when updating the reputational gain to a new level.

Figure F.11: Replication of Figure B.8 When Using Different Anchor Proxy Variables



Note: This figure shows that there are no other equilibria in counterfactual 7.3 for when everyone watches Fox News.

Figure F.12: Replication of Figure B.9 When Using Different Anchor Proxy Variables



Note: This figure shows that there are no other equilibria in counterfactual 7.3 for when no one watches Fox News.

G Full Survey Questionnaire

For brevity, we present a survey version for the RCT treatment group. The control group version does not have a module to watch the information RCT and to answer questions about RCT video and every other part remains the same.

We are a non-partisan group of researchers from Johns Hopkins University. You are being asked to join a research study. Participation in this study is voluntary. Even if you decide to join now, you can change your mind later.

RESEARCH SUMMARY (KEY INFORMATION) :

The information in this section is intended to be an introduction to the study only. Complete details of the study are listed in the sections below. The purpose of this research is to understand the social preferences of people living in the US. By participating in this survey, you contribute to important knowledge about social relations in the US. For the success of this research, **we need you to answer honestly**. If you are not sure about your answers, please give us your best estimates.

PROCEDURES:

If you agree to be in this study, we will ask you to do the following things: You will be asked some questions regarding your beliefs and attitudes. Also, you might watch a short video clip during the survey. We expect the survey to complete in about 15 minutes, including the time to watch the video clip.

You may be contacted in the future for a follow-up survey. You can decide whether to continue participating in this study at that point.

RISKS/DISCOMFORTS:

We do not anticipate any risks, including discomforts, greater than those encountered in everyday life.

BENEFITS:

This study may benefit society if the results lead to a better understanding of social relations in the US.

PAYMENTS:
If you satisfactorily complete the study, you will receive the participation reward promised in the survey invitation. Responses of low quality, however, will not qualify for the promised reward. You may receive an extra reward based on your responses.

VOLUNTARY PARTICIPATION AND RIGHT TO WITHDRAW:
You can agree to be in the study now and change your mind later, without any penalty or loss of benefits.

CONFIDENTIALITY:
Any study records that identify you will be kept confidential to the extent possible by law. The records from your participation may be reviewed by people responsible for making sure that research is done properly, including members of the Johns Hopkins University Homewood Institutional Review Board. Otherwise, records that identify you will be available only to people involved in this study.

IF YOU HAVE QUESTIONS OR CONCERNS:
You can ask questions about this research study now or at any time during the study, by emailing socialprefresearch@gmail.com.
If you have questions about your rights as a research participant or feel that you have not been treated fairly, please call the Homewood Institutional Review Board at Johns Hopkins University at (410) 516-6580.

IF YOU ARE HARMED BY PARTICIPATING IN THE STUDY:

If you feel that you have been harmed in any way by participating in this study, please email socialprefresearch@gmail.com. Please also notify the Homewood Institutional Review Board at Johns Hopkins University at (410) 516-6580.

Clicking **"Yes, I consent"** below means that you have read and understood the information in this consent form. Also, it means that you agree to participate in the study.
By consenting to this form, you have not waived any legal rights you otherwise would have as a participant in a research study.

- Yes, I consent.
- No, I do not consent.

→

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You have been selected to represent a portion of the US population. The results from the survey can influence political decisions and thus affect the lives of many people. In order for the information from this research to be the most helpful, it is important that you try to be as accurate, complete, and **honest as possible with your answers.** To do this, it is important to think carefully about each question, search your memory, and take time in answering. Are you willing to do this?

- Yes, I agree
- No, I do not agree

→

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What is your year of birth?

Which of the following best describes your ethnicity/race? Check all that apply.

- White
- American Indian or Alaska Native
- African American/Black
- Asian American/Asian
- Hispanic/Latino
- Other

→

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What is your gender?

- Male
- Female
- Other

What is your current marital status?

- Never Married
- Married
- Separated
- Divorced
- Widowed

What is **your** highest level of education?

- Less than high school degree
- High school graduate (high school diploma or equivalent including GED)
- Some college but no degree
- Associate degree in college (2-year)
- Bachelor's degree in college (4-year)
- Master's degree
- Doctoral degree
- Professional degree (JD, MD)

What was your **TOTAL household income in 2019 before tax**? Please indicate the answer in **USD ($, US dollar).** If your household did not have any income, please enter 0.

What was your **TOTAL household income in 2020 before tax**?
Please indicate the answer in **USD ($, US dollar).** If your household did not have any income, please enter 0.

→

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Do you use any of the TV services below to watch any news channels?

- Cable TV (Comcast, DirecTV, DishTV, Spectrum, Cox, etc)
- Internet Streaming Service (Sling TV, Youtube TV, Hulu TV, etc)
- Over-the-air signal (using TV antennas, or Locast)
- I don't watch TV news

→

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Who is your TV channel provider?

- Comcast (Xfinity)
- DirecTV (AT&T)
- Spectrum (Charter)
- Cox (Cox)
- Verizon Fios (Verizon)
- Dish TV (Dish Networks)
- Sling TV
- Youtube TV
- Hulu TV
- Other

Do you watch any of the following cable TV news channels? **Choose all that apply.**

- FOX News
- MSNBC
- CNN
- Other
- I don't watch any news channels

→

How many hours **per week** do you watch Fox News channel? Please give us your best estimate.

→

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Before we proceed, we have a question about how you are feeling.

Recent research on social preference shows that preferences are affected by context. Differences in feelings, knowledge, experience and environment can all possibly affect people's preferences and choices. It is crucial to our study that you actually take the time to read the questions. So the purpose of asking this question is to see whether you read the full instructions. Please go ahead and only check "None of the above" option as your answer, no matter how you are currently feeling. Thank you very much.

Please check all the words that describe how you are currently feeling.

- ☐ Happy
- ☐ Bored
- ☐ Excited
- ☐ Neutral
- ☐ Suspicious
- ☐ Anxious
- ☐ Peaceful
- ☐ Sad
- ☐ None of the above

→

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Please pay attention to the video on the next page, which will play for **58 seconds**. The video shows information about changing views on Asians. The information is from a survey done by the Pew Research Center.

We may ask a **question** about the video later. If you give a correct answer, you will receive a lottery to win a **reward**.

→

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If the video does not play automatically, **please press a play button and turn on the sound.** If you are viewing on a mobile phone, **rotate your screen** for a better view.

Proceed button will appear after you finish watching the video.

What percentage of US people hold unfavorable views against China in 2020? If you answer this question correctly, you will be given a lottery to receive an extra 100SB.

- 12%
- 31%
- 52%
- 73%

Did you have any technical difficulty in playing the video?

Did you have any technical difficulty in playing the video?

- Yes, I had difficulty.
- No, I did not have any difficulty.

→

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Please indicate your agreement with each of the following statements concerning immigration from China.

Strongly disagree				Neither agree nor disagree					Strongly agree	
0	10	20	30	40	50	60	70	80	90	100

Chinese immigrants get more from this country than they contribute. ☐ Not Applicable

The children of Chinese immigrants should have the same right to attend public schools in the U.S. as Americans do. ☐ Not Applicable

Chinese immigrants are contributing to the increase in crime in the US. ☐ Not Applicable

Chinese immigrants do **not** pose any health hazards to U.S. citizens. ☐ Not Applicable

For each of the items listed below, indicate what your attitudes are toward Chinese immigrants. My attitude toward Chinese immigrants is :

Strongly disagree				Neither agree nor disagree					Strongly agree	
0	10	20	30	40	50	60	70	80	90	100

Warmth toward them ☐ Not Applicable

Hatred ☐ Not Applicable

Acceptance Not Applicable

Dislike Not Applicable

→

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Please indicate your agreement with each of the following statements concerning the attitudes of **typical American citizens (below referred to as "people").**

Strongly disagree Neither agree nor disagree Strongly agree
0 10 20 30 40 50 60 70 80 90 100

Expressing hatred against Chinese immigrants harms one's social reputation. ☐ Not Applicable

People will appreciate it if someone states, "Chinese immigrants bring no good to the US!" ☐ Not Applicable

People will criticize if someone refers to the novel coronavirus as "China virus." ☐ Not Applicable

→

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Please indicate your agreement with each of the following statements concerning the attitudes of **typical American citizens (below referred to as "people").**

Strongly disagree				Neither agree nor disagree						Strongly agree
0	10	20	30	40	50	60	70	80	90	100

It is **not** shameful to publicly support to reduce the number of Chinese immigrants because they threaten our prosperity. ☐ Not Applicable

It is **not** socially acceptable to make a public statement that the US government should restrict the rights of Chinese immigrants. ☐ Not Applicable

It is socially acceptable to petition to deport Chinese immigrants if they have any Chinese government connections. ☐ Not Applicable

→

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Without specifying which ones you agree to, please report the total number of "yes" answers to the statements below. Your answer must be a number between 0 and 5.

- I am a veteran.
- I am living with at least one sibling in my household.
- I have a smartphone.
- I have health insurance coverage (of any kind, either public or private).
- Even though someone publicly says he/she dislikes Chinese immigrants, the person can still maintain good social relationships with most people.

→

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We want to ask about the device you are using to participate in this survey.

Some research says the survey mode can affect the survey responses. It is very important to have high-quality survey responses to obtain scientific results. The purpose of this question is to see whether you carefully read the full question. Please ignore the question and select "Other", regardless of the device you are using. Thank you very much.

Please choose the device you are using to participate in this survey.

- Desktop computer
- Laptop
- Tablet
- Mobile phone
- Other

→

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Suppose you can authorize us to donate $1 to any of the organizations below. Which organization would you like to authorize us to donate to? You don't have to pay anything if you decide to authorize.

Organization A is a think tank, which claimed that students and exchange scholars from China represent a great risk to the United States through their spying activities. **Organization A** advocates that the U.S. should restrict the entry of Chinese students and researchers.

Organization B is a think tank, which wrote a rebuttal policy report to the claim of Organization A. **Organization B** asserts that Organization A's claim is ungrounded and the Chinese students and researchers should not receive more penalty in immigration.

- I'd like to authorize a $1 donation to **Organization B.**
- I'd like to authorize a $1 donation to **Organization A.**

→

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Suppose there are two petitions, as described below. Would you like to sign any of the petitions?

Petition 1. Please Protect Chinese Immigrants' Safety and Rights

Many Chinese immigrants in the US are facing severe risks of being victims of hate crimes or discrimination, as a result of COVID-19 related fear. We should remember that the pandemic is **<u>not</u>** the fault of Chinese immigrants living in the US.

"We, the undersigned, call on the United States Congress and President of the United States to ensure the physical safety of Chinese immigrants as well as to protect their rights from discrimination"

Petition 2. Please Protect Our Country From Chinese Threats

From the COVID-19 pandemic, we have witnessed how the Chinese threatened our country's safety and prosperity. The Chinese immigrants bring **<u>no</u>** good to our country. It is time to reconsider whether it is beneficial to accept Chinese immigrants to the US.

"We, the undersigned, call on the United States Congress and President of the United States to review the current immigration policy for the Chinese and to continue making best efforts to protect our citizens' safety and interests from Chinese Threats."

--

- Yes, I want to sign **Petition 2. Please Protect Our Country From Chinese Threats.**
- Yes, I want to sign **Petition 1. Please Protect Chinese Immigrants' Safety and Rights.**
- No, I do not want to sign any petition.

→

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Now, you will be **randomly** matched with **two people** recruited for this study and you will play a game **twice** with your matched partners. All of your partners are currently living in the US.

You may receive extra rewards based on your responses.

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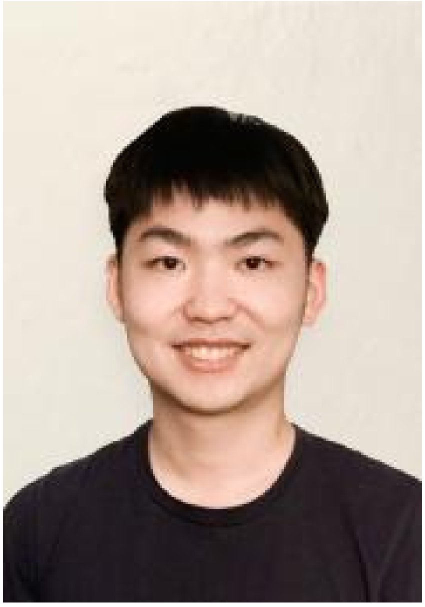
This is your first game. You are matched with the following person.



Name: Haozheng

You are given a lottery to win an extra reward of 100SB (=$1), which can be divided between you and your partner. **<u>10% of survey participants will win the lottery.</u>**

If you win the lottery, how much would you like to give to your partner? If you win, you will be **actually** paid 100SB net of your answer. For example, if you give 50SB to your partner and if you are selected, then you will be paid 50SB (=100SB - 50SB).

<u>Your answer will not affect your probability of winning the lottery.</u>
Please move the slider below to enter your amount to **give** to your partner.

0 10 20 30 40 50 60 70 80 90 100

This is your second game. You are matched with the following person.

Name: Peter

You are given a lottery to win an extra reward of 100SB (=$1), which can be divided between you and your partner. ***<u>10% of survey participants will win the lottery.</u>***

If you win the lottery, how much would you like to give to your partner? If you win, you will be ***actually*** *paid 100SB net of your answer. For example, if you give 50SB to your partner and if you are selected, then you will be paid 50SB (=100SB - 50SB).*

<u>Your answer will not affect your probability of winning the lottery.</u>
Please move the slider below to enter your amount to ***give*** *to your partner.*

0 10 20 30 40 50 60 70 80 90 100

Below is a 10-point scale on which the political views are arranged from extremely liberal (left) to extremely conservative (right). Where would you place yourself on this scale?

Most Liberal										Most Conservative
0	1	2	3	4	5	6	7	8	9	10

Political views on **Social Issues** ☐ Not Applicable

Political views on **Economic Issues** ☐ Not Applicable

→

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Who did you vote for in the 2020 presidential election?

- Donald Trump
- Joe Biden
- Someone else
- I did not vote
- Refuse to answer

Who did you vote for in the 2016 presidential election?

- Donald Trump
- Hillary Clinton
- Someone else
- I did not vote
- Refuse to answer

→

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Which town, county and state in the US were you living in when you were aged 14? If you were living abroad, please enter the country where you were living.

→

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Please indicate ethnicity of your current best friends (whom you have known for more than 1 year) in the order of your favorites.

	Non-Hispanic White	Black or African American	Hispanic or Latino	Native American or Alaskan Native	Chinese	Other Asian	Native Hawaiian or Pacific Islander	Other
Best Friend 1	○	○	○	○	○	○	○	○
Best Friend 2	○	○	○	○	○	○	○	○
Best Friend 3	○	○	○	○	○	○	○	○

→

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What fraction of your classmates were **East Asians** in your primary, secondary, high school, and college? If you did not attend any of these schools, please check "Not Applicable".

	No Asians 0%	More than 0% less than 2%	More than 2% less than 5%	More than 5% less than 10%	More than 10%	Not applicable
Primary school	○	○	○	○	○	○
Secondary school	○	○	○	○	○	○
High school	○	○	○	○	○	○
College	○	○	○	○	○	○

→

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Have you got infected by COVID-19?

- Yes
- No
- I refuse to answer

Do you have anyone close to you (family, relatives, friends) who got infected by COVID-19? Choose all that applies.

- Yes, family member(s)
- Yes, relative(s)
- Yes, friend(s)
- No, I do not have anyone close to me who got infected by COVID-19
- I refuse to answer

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Which statement best describes **<u>your</u>** current employment status?

- Employed (Wage earner)
- Self-employed
- Not employed
- Not applicable

→

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Were **you** working between January 2020 and March 2020? If **you** were temporarily off from your work but had a job, please answer yes.

- Yes
- No
- I refuse to answer

→

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Which industry did **you** work in between January 2020 and March 2020? If **you** had multiple jobs, please answer using your last job during the period. If you don't know which one to choose, please click "Other" and describe it in the text box.

- Agriculture or Farming
- Mining or Logging
- Construction
- Manufacturing
- (Wholesale / Retail) Trade, Transportation/Warehousing, Utilities
- Information
- Finance and Insurance, Real Estate and Rental and Leasing
- Professional, Scientific, Technical Services, Management, Administrative Services
- Education Service, Health Care and Social Assistance
- Arts, Entertainment, Recreation, Accommodation, Food Services
- Other Services except Public Administration
- Federal/State/Local Government
- Other
- Not applicable

→

How did the Pandemic affect the job **you** held between January and March 2020? If **you** had multiple jobs, please answer using your last job during the period.

- ○ I could continue working in the job, and I could work mostly **at home.**
- ○ I could continue working in the job, but I had to work mostly **face-to-face.**
- ○ I lost the job due to pandemic.
- ○ I refuse to answer.

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In which state do you currently reside?

What is your 5-digit ZIP code?

→

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Do you have a Twitter account?

- Yes
- No

→

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We hope to understand public views during the COVID-19 pandemic.

For research purposes, would you like to share your **Twitter username**? The username consists of alphanumeric characters and comes after @ sign. e.g. @(username).

If you share your Twitter username, you will be given a lottery to win an **extra 2000SB (=$20)** compensation. We will randomly select 5 people who provide a valid Twitter username and pay them the extra compensation. We do not have an accurate prediction for how many people will be willing to share their Twitter usernames, but we plan to invite 3000 participants to this study.

We assure you that there is absolutely **no** risk of losing confidentiality from sharing your Twitter username because we will **never** quote an individual username nor a single tweet without changing it. We will present aggregate statistics or summary keywords or phrases only from the Twitter data, which do **not** reveal the identity of any single Twitter user.

- Yes, I'd like to share my Twitter username for research.
- No, I do not want to share my Twitter username for research.

→

What is your **Twitter username**? The username consists of alphanumeric characters and comes after @ sign. e.g. @(username).

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Do you think this survey is biased in favor of or against Chinese immigrants?

- I feel this survey is biased in favor of Chinese immigrants
- I feel this survey is neutral
- I feel this survey is biased against Chinese immigrants
- I refuse to answer

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Thank you for participating in our survey.

You can find more survey information from the following website. The survey you just participated in is labeled as "Main Survey" on the website, which is to be done in March, 2021.
https://sites.google.com/view/socialprefresearch

If you have any questions, please feel free to send an email to socialprefresearch@gmail.com

To complete this survey, please proceed to the next page.

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