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Competition Between Friends and Foes

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Competition between friends and foes*

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While social preferences have been shown to be an important predictor in economic decision making it has been largely ignored in describing auction behavior. We build on theoretical models of spiteful bidding to test experimentally whether the rival's type impact bidding behavior in an auction. For that purpose, we collect data on competitions – in form of first-price auctions – between Donald Trump and Hillary Clinton voters. We show that the rival's type – i.e., the competitor supports the same candidate (i.e., friend) or the competitor supports another candidate (i.e., a foe) – influences auction behavior. Clinton voters compete more aggressively against Trump voters compared to fellow Clinton voters, in line with the theory on spiteful bidding. Trump voters, on the other hand, do not compete more aggressively against Clinton voters compared to fellow Trump voters. This behavior still prevails even if we account for beliefs. Using data on attitudes suggest that spite might be driving this behavior. We conclude that preferences over the opponent seem to influence behavior even in a competitive setting.

Keywords: Spite, Auction, Competition, Experiment, Donald Trump, Hillary Clinton JEL: D44, C57, D72, C92

1. Introduction

Competition is part of everyday life. We constantly compete for power, resources, recognition, and more. In markets a common form of competitions are auctions. Auctions are commonly used as selling mechanisms, and we find explicit auction institutions in many markets. For example in online auctions (like eBay), government auctions (like spectrum auctions), at charity events (like silent auctions), etc.

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After the early investigations on auctions by Vickrey (1961) many extensions of the standard risk-neutral selfish-agent model have been suggested. Rather early on Cox et al. (1985, 1988) suggested a model accounting for risk-aversion by subjects. After the rise of experimental economics many additional model extensions have been introduced to cope with new experimental evidence on overbidding – i.e., real bids are higher than risk neutral Bayesian Nash-equilibria. For example Filiz-Ozbay and Ozbay (2007, 2010) suggest anticipated regret as a motive to explain overbidding. Cooper and Fang (2008) suggest joy-of-winning. Güth et al. (2003), Dittrich et al. (2012), and Ockenfels and Selten (2005) relate bidding behavior to learning. Anderson et al. (1998) introduce bounded rationality in auctions. However, most models do not account for social preferences.[1] Rather recently, Morgan et al. (2003), Mill (2017), Bartling et al. (2017), and Kirchkamp and Mill (2019) used theoretical means to relate spiteful preferences (as a form of negative social preferences) to overbidding in auction settings.[2] Besides these few investigations, social preferences have been largely ignored in the auction literature. However, it seems very plausible that behavior in auctions is also driven by social preferences, as people constantly compete with people they know, with their friends and enemies. Also, firms might have shared interests (e.g. cross-shareholdings) or conversely might even compete in a spectrum auction against their rival company. It is simple to imagine that competitions between enemies are more aggressive than competitions between allies. In a competition against an ally, one might be happy for the ally to win - at least the ally supports the same ideal or one even holds shares of the competitor- and therefore, compete less aggressively. In a competition against an enemy, however, one might feel additionally unhappy if the enemy wins. Thus, we want to study whether the competitor – either a friend or a foe – influences the behavior of subjects in the standard auction setting.

This investigation has obvious links to the area of group conflict, discrimination[3] and also group contests in general.[4] For example, Filippin and Guala (2013) demonstrate experimentally that costless discrimination in favor of the ingroup is present in markets. Similarly, Li et al. (2011) study how subjects behave in an oligopoly market if subjects are assigned to different groups by using the minimal group paradigm and Chowdhury et al. (2016) examine the effect of minimal identity and real identity (race) on group conflict and show that real identity leads to more group conflict.[5] Even though group-identity has been extensively studied in relation

[1] Some important exceptions are: Brandt et al. (2007), Mill (2017), Morgan et al. (2003), Sandholm and Sharma (2010), and Sandholm and Tang (2012) who suggest spite as a theoretical model extension and Klor and Shayo (2010) and Shayo (2009), and similarly Klose and Kovenock (2015) and Varma (2002), suggest social identity and identity dependent externalities as model extensions. Bartling and Netzer (2016), Bartling et al. (2017), Kimbrough and Reiss (2012), and Kirchkamp and Mill (2019) provide some experimental (but not causal) evidence indicating spite in auctions.

[2] Several empirical studies have shown spiteful preferences to be rather common (Andreoni, 1989). For example, Abbink and Sadrieh (2009) and Abbink and Herrmann (2011) show in experiments that subjects display nasty and antisocial behavior. Additionally, a rather early investigation by Levine (1998) demonstrates that 20% of subjects might be considered spiteful, and very famously Fehr et al. (2008) show that a surprising amount of spiteful behavior can be found in some regions in India.

[3] See De Dreu (2010), De Dreu et al. (2016), Filippin and Guala (2013), Halevy et al. (2008), Weisel and Böhm (2015), and Weisel and Zultan (2016).

[4] For an extensive overview see Sheremeta (2017).

[5] We further know however, how identity or the presence of e.g. superstars impact behavior (Brown, 2011, see). We also now that group identity has adverse effects on trade behavior in markets (Heap and Zizzo, 2009), that group identity increases competitive behavior in competitive problem solving tasks (Cornaglia et al., 2019) and that group identity seemingly has no effect on behavior in tug-of-war games (Huang et al., 2020).

to between-group conflicts (see Akerlof and Kranton, 2000; Chen and Li, 2009; Kranton and Sanders, 2017) an open question is still how group-identity influences auction behavior. In particular, it is unknown how behavior in an auction (as a special form of a competition) is influenced by the competitor's type (friend or foe). This paper aims to answer this question.

Friends and foes can come in many shapes. Friends might be personal friends, family, but it also can be people with similar ideals and interests, it can be people with similar goals who for example support the same team or candidate, it also might be a befriended manager or even a company having common interests; foes, on the other hand, might not only be annoying colleagues but can also be supporters of an opposing party, supporters of legislation one is against and even competing companies on a tough market. Especially, political rivalry conceivably is significant in many situations. Not agreeing on a federal budget and shutting down the government can be one of the consequences if foes are competing over power. Using filibusters and not confirming cabinet members conceivably is another negative consequence of competitions between foes. Some papers even show that partisanship affects non-political behavior. For example, Fowler and Kam (2007) demonstrates that partisanship influences decisions in dictator games. They show ingroup favoritism among co-partisans, in the sense that dictators share more money with copartisan recipients than non-partisans. In similar vain Carlin and Love (2013) investigate the effect of partisanship on trust behavior. They show that similar to the literature on ingroup favoritism, partisanship biases trust behavior in favor of co-partisans. Our paper contributes to this literature in the sense that we also study the effect of partisanship on non-political behavior in particular in a competition setting.

Besides few theoretical papers suggesting spite and social identity as a motive for auction behavior, the empirical auction literature has largely not taken social preferences, and in particular the opponent, into account even though there is plenty of evidence that partisanship impacts behavior,[6] that group identity might influence market outcomes[7] and that social preferences are present in many decision-making situations. To the best of our knowledge, there is no *empirical* evidence of whether the identity of the opponent – either a friend or enemy – influences auction behavior and more generally there is hardly any investigation on whether social preferences matter in auctions.[8]

Hence, the aim of this paper is to investigate whether subjects compete more aggressively against foes than against friends. For that purpose, we recruit Donald Trump and Hillary Clinton voters[9] and observe bidding behavior in a first-price winner-pay auction.[10] In this study, we refer to subjects who vote for the same presidential candidate as *friends* and subjects who vote for the alternative candidate as *foes*.

[6]See for example Carlin and Love (2013), Fowler and Kam (2007), and Li et al. (2011).

[7]See for example Brown (2011), Cornaglia et al. (2019), Heap and Zizzo (2009), and Huang et al. (2020).

[8]Note, however, that there exists a literature accounting for social preferences (Brandt et al., 2007; Kirchkamp and Mill, 2019; Mill, 2017; Morgan et al., 2003) , social identity (Klor and Shayo, 2010) and identity depended preferences (Klose and Kovenock, 2015; Varma, 2002) in their *theoretical* models.

[9]During the 58$^{\text{th}}$ presidential election there were obviously also several other viable candidates other than Donald Trump and Hillary Clinton. However, the Democratic and Republican party together collected roughly 94% of the votes and hence we consider the two respective candidates as the main competitors for our study.

[10]We use the first-price auction as it is widely used, echos key features of competitive environments, and is arguably, one of the simplest auctions to understand for participants.

We show that Clinton voters bid more aggressively – i.e., exhibit higher bidding slopes – against Trump voters compared to competitions against fellow Clinton voters. The shape of the bidding function is surprisingly similar to the theoretically predicted bidding function of a spiteful bidder. However, these effects do not hold for Trump voters, who bid less aggressively – i.e., exhibit smaller biding slope – against Clinton voters compared to competitions against fellow Trump voters. These results cannot be fully explained by the subjects' beliefs as Clinton voters have the same belief over the opponents' bidding function for both friends and foes. Trump voters, however, expect Clinton voters to bid more aggressively.

Using attitudinal measures, we can show that the bidding behavior might be explained by attitudes. Clinton voters bid again more aggressively if they dislike their opponent. This effect does not hold for Trump voters. Overall, subjects' expected payoffs are 6% less if they compete against foes compared to subjects who compete against friends.

These results are hard to reconcile with typical models of auction behavior (i.e., risk aversion, joy of winning, learning, anticipated regret, etc.) as these models typically do not take preferences over the opponent into account. Therefore, a model is needed accounting for social preferences. We suggest that a model accounting for spiteful preferences might be a useful extension of the typical models of auction behavior.

The main contribution of this paper is to provide empirical evidence that subjects sometimes bid more aggressively in auctions if competing against a foe. This substantiates the importance of social preferences in auctions.

The remainder of the paper is structured as follows: In Section 2 we will explain the design of the experiment. Section 3 presents the model. Section 4 shows the results of the experiment. Section 5 concludes.

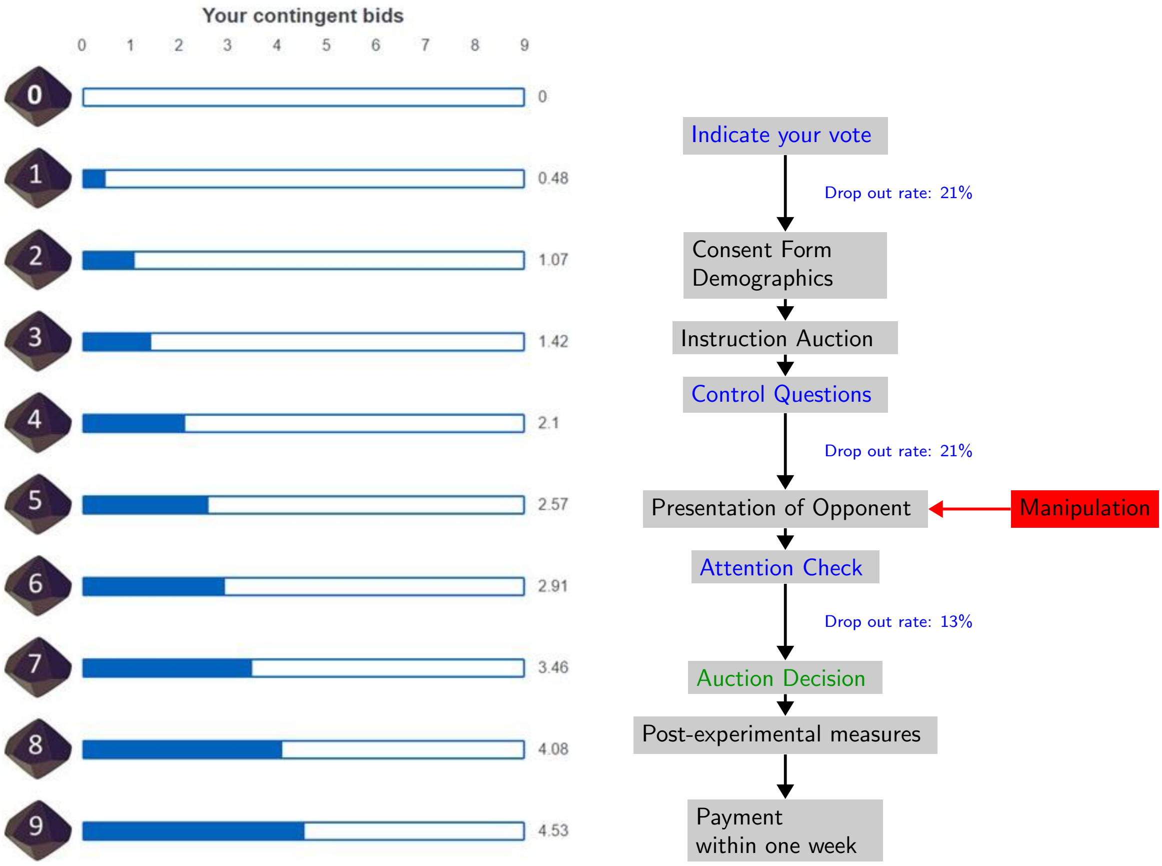
2. Design of the experiment

To test how friends and foes will compete, we elicited the bidding behavior of subjects matched with friends and foes in a first-price auction. We decided for a first-price auction as this is, arguably, one of the simplest auctions to understand for participants. Further, this auction is widely used and echos key features of competitive environments, enabling us to extrapolate and generalize our results to other competitive settings.

To manipulate the opponent type, we matched Donald Trump and Hillary Clinton voters to compete against either people who voted the same way (friends) or voted differently (foes). We stipulate that people who voted the same way were considered friends and opposing voters were considered foes.[11]

We expected that it might be difficult to find sufficiently many Trump voters within the standard student sample; therefore, we decided to conduct the experiment online to attract as many Trump voters as possible. Therefore, we recruited subjects via Amazon's Mechanical

[11] Given the rhetoric during the campaign and also after the election of both Hillary Clinton and Donald Trump, we find it plausible to assume that opposing voters are considered less positive than voters who voted the same.



(a) Screenshot of the conditional bidding decision in the experiment.

(b) Structure of the experiment.

Figure 1: Screenshot and structure of the experiment.

Turk (MTurk)[12] which is an online labor market and frequently used by social scientists for experiments.[13]

Recruited subjects were transferred to Qualtrics (an online survey tool) to take part in the experiment. At arrival, subjects were first asked their unique MTurk-ID and then asked to indicate their vote in the 58th US presidential election. Only subjects who indicated to be a voter for either Donald Trump or Hillary Clinton were directed towards the consent form.[14] As we do not have clear predictions for undecided or independent voters, we excluded them from participation in the survey, and the survey ended for them directly after indicating their vote. All remaining subjects were directed, after giving consent, to answer socio-demographic questions (gender, age, income, education).

Hereafter, subjects were presented the auction instructions.[15] To have a clean design and to avoid bore-out effects, we implemented the auction as a single shot game using a strategy-method like approach (see Figure 1a). To test our theoretical predictions it is essential to measure the

[12]Appendix A.1 gives a brief summary of the main MTurk features.

[13]For example : Horton et al. (2011), Jordan et al. (2017), Jordan et al. (2016), Mao et al. (2017), Peysakhovich et al. (2014), Rand et al. (2014), and Suri and Watts (2011). See Arechar et al. (2018) for a comparison between lab and online experiments, indicating that the results obtained from MTurk-experiments are very similar to the ones obtained in the lab.

[14]79 % of the arriving subjects were eligible to take part in the experiment.

[15]The original instructions can be found in Appendix D.1.

functional form of the bidding behavior. Thus, subjects were told that their valuation for a commodity X will be determined by a ten-sided die with valuations $v \in \{\$0, \$1, \$2, ..., \$8, \$9\}$. The instructions also stated that the same mechanism would be applied to their opponent but with an independent second die. It was explained to subjects that their payoff would depend on their decision and the decision of their opponent and also on the two die rolls. The payoff of subjects was determined by the rule of a first-price auction.

Thus, subject i receives the following payoff $\Phi(\beta_i, v_i)$ as a function of his realized valuation v_i and his bid $\beta_i(v_i)$:

$$\Phi(\beta_i, v_i) = \begin{cases} v_i - \beta_i(v_i) & \text{if } \beta_i > \beta_j \text{ } (i \text{ wins}) \\ \frac{v_i - \beta_i(v_i)}{2} & \text{if } \beta_i = \beta_j \text{ (a tie)} \\ 0 & \text{if } \beta_i < \beta_j \text{ } (i \text{ loses}) \end{cases} \tag{1}$$

where β_i is subject i's bid and β_j is the bid of the opponent.

Subjects were told that after finishing the experiment, the valuations would be determined and they would be paid within one week. After reading the instructions, subjects were asked four control questions to ensure understanding. All subjects failing to answer the control questions correctly were not allowed to proceed with the experiment.

Hereafter, subjects were presented with the experimental manipulation. The manipulation of the experiment was to let subjects either interact with a friend (somebody who voted the same way) or a foe (somebody who voted for the competing candidate). Consequently, we implemented a 2 $\times$ 2 design (Opponent $\times$ Vote), with Opponent $\in$ {Friend; Foe} and Vote $\in$ {Clinton; Trump}.

More specifically, subjects were told, that at the beginning of the experiment Trump voters were assigned the group color red, while Clinton voters were assigned the color blue. The manipulation was to tell subjects which color their matched opponent will have (either red or blue).[16]

To test comprehension and attentiveness, we asked whether subjects understand the elements that appear on her screen, as some recent studies indicate the use of bots on Mturk. These simple questionnaire-elements include choices, payoffs, as well as information of her coplayer, i.e., whether their matched competitor was assigned the color blue, red or green (which was a filler). Inattentive subjects, those not comprehending the task, as well as potential bots were filtered out, as we are only interested in subjects who have a basic comprehension of the task. Thus, failing to answer these questions correctly led to the exclusion of the experiment and the payment.[17]

One potential concern of asking – as a basic comprehension test – which color the competitor was assigned to, might make the manipulation salient. There are several responses to this concern. First, it is crucial for this study that subjects have a basic comprehension of the task and the situation. Second, there have been several comprehension questions which would

[16] To ensure assignment subjects were also told that it might happen that multiple subjects are assigned to one subject in determining the payoff.

[17] Excluded subjects were not allowed to continue the experiment; hence, we also do not have their decisions. 32 % of eligible subjects failed either the testquestions or the manipulation check.

diffuse the focus on this particular manipulation question.[18] Third, even if the question would result in a higher salience for the political position of the opponent, this would just result in a more realistic setting. Political attitudes and views are often presented and highlighted very saliently by real-world actors, as setting up yard signs, having political bumper stickers, wearing MAGA-hats, etc.[19]

All subjects who answered the control questions and the manipulation question correctly were then asked to indicate their bidding function conditional on all their possible die rolls (valuations).[20] Thereafter, subjects also indicated their conditional bidding belief.[21]

After the auction decision subjects had to answer several post-experimental questions.[22] In particular, we elicited attitudes of subjects towards their opponent by using two measure of attitude: the social distance questionnaire (Crandall, 1991)[23] and the feeling thermometer (Weisberg, 1980).[24] Both measures are discussed in more detail in Appendix B. The structure of the experiment can be seen in Figure 1b.

After completing the experiment subjects were informed that they would be paid within one week after determining the payoff.

3. Model

To have specific predictions how the type of the opponent (foe vs. friend) influences behavior we base our economic model on the theory of spiteful behavior.[25] That means, we assume

[18] Note: even if experimenter demand is indeed induced it is unlikely that the effect is very strong. Quidt et al. (2018) estimate the demand effect for dictator games in case the experimenter explicitly tells participants what to do at less then one standard error. In case the experimenter just indicates his expectation the demand effect is estimated at about .2 standard errors. In our experiment participants *might* expect the demand to be a change in behavior. However, the auction allows for several ways of doing so and thus, a demand effect would be even more restricted.

[19] The motivation of people engaging in such behavior in real life is manifold, and some motives might raise concerns for the research question if subjects could endogenously choose how strongly to signal their attitude. However, the strength of the signal was kept constant across treatment as subjects were merely informed about the voting decision of their opponent.

[20] The instruction can be found in Appendix D.1.

[21] The bidding belief was elicited only in the third and fourth wave. See Appendix D.3 for the corresponding instructions.

[22] In the post-experimental questions we elicited attitudes towards the opponent, spiteful behavior, spiteful attitudes in general, and prosocial behavior. Spiteful behavior and the effects of attitudes on this behavior is discussed in a separate paper (see Mill and Morgan, 2018) with the goal to investigate attitudes, spite, and partisanship. The reason we do not combine both papers is threefold: 1) both papers are aimed at a different audience, 2) combining both papers would make the paper too long and most importantly, and 3) the paper would lose its focus as both papers are aimed at very different questions.

[23] The social distance questionnaire is designed "to measure social rejection and willingness to interact with an individual member of a social group"(Robinson et al., 1999, p. 341 ff).

[24] The feeling thermometer asks subjects to imply how warm they feel towards a specific group or person.

[25] Note: An alternative approach would be to directly use a model of social identity as e.g., in Klor and Shayo (2010) and Shayo (2009) or a model of identity dependent externalities as suggested by Klose and Kovenock (2015) and Varma (2002). However, using the model by Klor and Shayo (2010) results in the same predictions as using the model by Morgan et al. (2003). More specifically, we could assume that subjects obtain an additional utility if the payoff of the ingroup is increased by a function $\nu(x)$ and obtain a negative payoff if the payoff of the outgroup is increased by a function $\mu(x)$. As we consider only an auction with two bidders, both cases will never occur simultaneously. If we assume a simple function of the form $\mu(x) = m$ for outgroup hate, we can derive the same equilibrium behavior in case of outgroup hate as we do with spiteful preferences, i.e., outgroup hate leads to a bidding function described in Equation 5 with $\alpha = m$. If we focus on ingroup love and assume a simple function of the form $\nu(x) = n$ we can derive the same equilibrium behavior in case of ingroup love as we do with spiteful preferences, i.e., ingroup love leads to a bidding function of the form in

that bidders either do not care about their opponent (the standard risk neutral selfish theory benchmark) or do care negatively about their opponent, in the sense that the more the opponent gets, the less utility the bidder derives.[26] Note, that standard explanations for bidding behavior as risk-aversion, anticipated regret, joy of winning, learning, etc. would not be appropriate models here as they would not predict any changes. More specifically, all those models assume subjects to care only about their own personal payoff with additional constraints or extensions on their own personal payoff, ignoring the payoff of the other bidders. Hence, to predict changes in bidding behavior due to the opponent type, some sort of social preferences are required.

Here we use the same economic model of spiteful behavior as in Morgan et al. (2003). We will present the model for the two-bidder case only, as the experiment is conducted in two-bidder settings. For the n-bidder scenario see Morgan et al. (2003).

Let us assume that two bidders, i and j, compete for a single object in a first-price auction. Let us further assume that every subject values the object with v_k with $v_k \sim F(0, \overline{v})$ and $k \in \{i, j\}$, while F is a distribution function with finite support and f denotes the associated density of F with support $[0, \overline{v}]$. Different from models with selfish risk-neutral subjects we assume that a spiteful subject, in case she does not receive the object, has a concern for the surplus of the rival bidder. This concern is the surplus the winning bidder obtains weighted by the spite factor $\alpha \in [0, 1]$. All subjects submit a bid b_k following a monotonic bidding function $\beta_k(v_k)$ with first derivative $\beta'(x) \equiv \frac{d\beta(x)}{dx}$ and inverse $\beta_k^{-1}(b_k) = v_k$.

The utility of player i is as follows:

$$\Phi(\beta_i, v_i) = \begin{cases} u(v_i - \beta_i(v_i)) & \text{if } \beta_i > \beta_j \text{ } (i \text{ wins}) \\ u(\frac{v_i - \beta_i(v_i)}{2}) & \text{if } \beta_i = \beta_j \text{ (a tie)} \\ u(-\alpha(v_j - \beta_j(v_j))) & \text{if } \beta_i < \beta_j \text{ } (i \text{ loses}) \end{cases} \tag{2}$$

We follow the standard approach and assume that bidder i with valuation v_i makes a bid b. The expected utility of this bidder is given as follows:

$$\mathbb{E}(b, v) = \underbrace{\int_0^{\beta_j^{-1}(b)} u(v - b) f(v_j) dv_j}_{\text{bidder } i \text{ wins and obtains the prize}} + \underbrace{\int_{\beta_j^{-1}(b)}^{\overline{v}} u(-\alpha(v_j - \beta_j(v_j))) f(v_j) dv_j}_{\substack{\text{bidder } i \text{ loses} \\ \text{and experiences spite}}} \tag{3}$$

For simplicity we assume $\overline{v} = 1$, $u(x) = x$, and a symmetric equilibrium bidding function. Differentiating Equation 3 with respect to b and letting $\beta(v) = b(v)$ yields, after some rearrangement, the following:

$$b'(v) = \left[\frac{(1+\alpha) \cdot f(v)}{F(v)}\right] v - \left[\frac{(1+\alpha) \cdot f(v)}{F(v)}\right] b(v) \tag{4}$$

Solving the ODE (4) with the initial value $b(0) = 0$ we obtain the symmetric equilibrium

Equation 5 with $\alpha = \frac{-n}{2+n}$. Thus, all our results can be interpreted in the context of social identity and also in the context of spiteful preferences alike.

[26] Note that while we focus on antisocial preferences in the form of spite, we could have also focused on prosocial preferences in the form of altruism. The theoretical predictions would, however, not change as altruism is basically the flip side of spite.

bidding function b^α:

$$b^\alpha(v) = v - \frac{\int_0^v F(t)^{1+\alpha} dt}{F(v)^{1+\alpha}} \tag{5}$$

Equation 5 becomes the familiar equilibrium bidding function for the first-price auction with two bidders if $\alpha = 0$:

$$b^{\alpha=0} = v - \frac{\int_0^v F(t)\, dt}{F(v)} \tag{6}$$

In the experiment we use a uniform distribution function. In that case Equation 5 becomes:

$$b^\alpha_{F(v)=v} = v \cdot \left(\frac{1+\alpha}{2+\alpha}\right) \tag{7}$$

Figure 2 shows the theoretical equilibrium for the first-price auction with two spiteful bidders.

Proposition 1. *A symmetric equilibrium for the first-price auction with two spiteful bidders is:*

$$b^\alpha(v) = v - \frac{\int_0^v F(t)^{1+\alpha} dt}{F(v)^{1+\alpha}} \tag{8}$$

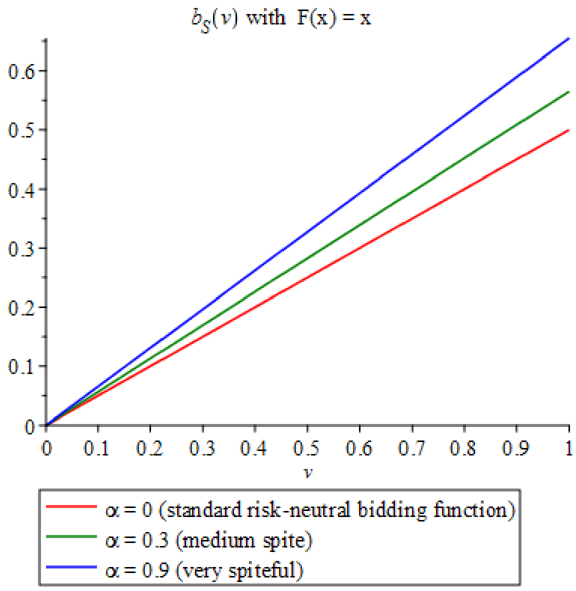


Figure 2: Equilibrium bidding behavior, with various spite factors, in a first-price auction in a two bidder setting with uniform distributed valuations.

It is easy to see that $b^\alpha(v)$ is increasing in α by differentiating $b^\alpha(v)$ with respect to α:

$$\frac{\partial b^\alpha(v)}{\partial \alpha} = -\frac{\int_0^v F(t)^{1+\alpha} \cdot ln(\frac{F(t)}{F(v)})dt}{F(v)^{1+\alpha}} \geq 0 \tag{9}$$

Similarly it can be shown that $b^\alpha(v)$ is increasing in v

$$\frac{\partial b^\alpha(v)}{\partial v} = \frac{\int_0^v F(t)^{1+\alpha}\, dt}{F(v)} \cdot \frac{f(v)(1+\alpha)}{F(v)^{2+\alpha}} \geq 0 \tag{10}$$

Again differentiating 10 with respect to α it can be seen that the derivative of $b^{\alpha}(v)$ with respect to v is increasing in α:

$$\frac{\partial \frac{\partial b^{\alpha}(v)}{\partial v}}{\partial \alpha} = \frac{f(v)}{F(v)^{2+\alpha}} \cdot \left[\int_0^v F(t)^{1+\alpha}\, dt + (1+\alpha) \int_0^v F(t)^{1+\alpha} \ln\left(\frac{F(t)}{F(v)}\right) dt \right] \geq 0 \tag{11}$$

Corollary 1. *The derivative of the symmetric equilibrium bidding function with respect to valuation is increasing in spite.*

Predicting the behavior in the auction we hypothesize that subjects will follow, on average, the bidding function of Equation 7. In particular, we assume that subjects have an average spite factor $\overline{\alpha}$. However, we expect that subjects who are assigned a foe as competitor have a spite factor bigger than $\overline{\alpha}$. Hence, following the model, we expect that subjects who compete against foes have a steeper bidding slope than subjects competing against friends (due to an increased α). If subjects indeed follow Equation 7 we would expect no difference between subjects competing against friends or against foes for a valuation of zero (as the bidding function is zero for a valuation of zero for all factors of α), i.e., the intercept is predicted to be zero.

Therefore, we derive the following hypotheses:

Hypothesis 1.1. *The bidding function of subjects competing against foes is steeper than the bidding function of subjects competing against friends, due to a larger α.*

Hypothesis 2.1. *The intercept of the bidding function should not differ for subjects competing against foes compared to subjects competing against friends.*

4. Results

4.1. Participants and Demographics

We conducted the experiment in four waves: in late November 2016 (before the 58th US presidential election), late January 2017 (after the inauguration), late October 2018 (before the midterms) and early November 2018 (after the midterms).[27] We recruited 5973 participants with the online labor market Amazon Mechanical Turk. 2616 participants finished the survey. The experiment was implemented using the online survey tool Qualtrics. The entire experiment lasted on average for about 20.4 ($SD = 12.87$) minutes. Participants earned on average \$2.07 resulting in an average hourly wage of \$7.36 , which is more than the median hourly income of an average MTurker.

As with most experimental studies, our final sample does not perfectly represent the American population.[28]

[27] The experiment was conducted simultaneously to another experiment (reported in Mill and Morgan, 2018) where it was of essence to conduct the experiment before the 58th US presidential election and after the inauguration. The second set of waves (before and after midterms) was conducted to assess subjects beliefs. For the current paper we do not have any predictions of the timing on bidding, and as the bidding data does not differ significantly between the waves, we pool the data over the time dimensions. However, if we would not pool the data, the results would still be very similar.

[28] For comparison estimates see the census aggregates: `https://www.census.gov/quickfacts/fact/table/US/PST045216` and `https://www.census.gov/content/dam/Census/library/publications/2016/demo/p20-578.pdf`. The subsequent summary statistics are shown only for those participants who completed the study.

The ages of our participants ranged from 18 to 88 years, with most subjects in the age between 30 and 44 (48 %) and 24 %, 24 % of subjects in the age between 18 and 29, 45 and 64, respectively (Median = 36). Hence, our sample is younger than the average American with a median age of 37.9 and with 15% of the population older than 65 years (compared to 4 % in our sample).

In addition, 55 % of our participants were female compared to 50.8% females in the US population.

Concerning the ethnicity in our sample: 82 % of subjects are White; 6 % of subjects are African American; 4 % of subjects are Hispanic and 6 % of subjects are Asian compared to 61.3% Whites; 13.3% African Americans; 17.8% Hispanics and 5.7% Asians in the US population.

Moreover, our participants indicated to have higher education than the typical American. 69 % of subjects implied to have at least a Bachelor's degree as the highest qualification compared to roughly 33% in the United States as a whole.

Hence, our sample is younger, more female, more white and better educated than the average American.

In addition, looking at the location of the subjects (see Figure 3), we find that the subjects mainly come from populated and urban areas. This can also explain the discrepancy in distribution of Trump and Clinton voters in our study (38 % vs. 62 %) compared to the distribution in the general election (46 % vs. 48 %).

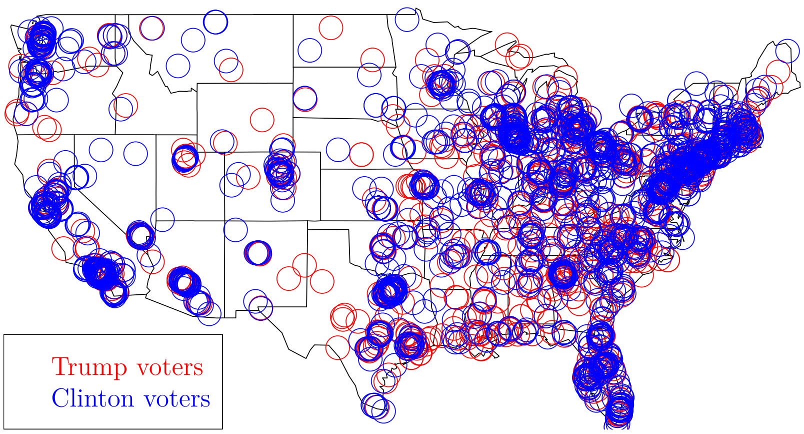


Figure 3: Participants' location by vote.

Nevertheless, the subjects in our study exhibit similar demographic voting patterns as reported in pollings[29]: Trump voters are significantly less educated than Clinton voters. Further, Trump voters in our sample are on average significantly older than Clinton voters. Further, the fraction of white people is significantly larger for Trump voters compared to Clinton voters. Also more men voted for Donald Trump (which however, is not significant in our sample). Table 1 shows the demographic differences between Clinton and Trump voters in our sample.

[29]See Alcantara et al. (Oct. 16, 2016) or Kirk and Patrick (Nov. 7, 2016).

Table 1: Demographics of participants.

Test	Clinton voters ($N = 1621$)	Trump voters ($N = 995$)	T	Df	p	95% CI	Sign.
Female	0.56	0.53	1.39	2614.00	0.17	[-0.01 , 0.07]	
Age	37.72	40.18	-5.14	2614.00	0.00	[-3.39 , -1.52]	* * *
Race=White	0.79	0.88	-6.07	2614.00	0.00	[-0.12 , -0.06]	* * *
College-Ed or Higher	0.76	0.66	5.75	2614.00	0.00	[0.07 , 0.14]	* * *
Income > $70k	0.43	0.47	-1.80	2614.00	0.07	[-0.08 , 0]	

We use two sample t-tests to compare characteristics $^{*}p<0.05;^{**}p<0.01;^{***}p<0.001;$

Even though our sample does not fully represent the typical American, we are able to show the same tendencies as in the American population. Accounting for our selected sample[30] we see that Trump voters in our sample reflect Trump voters in the general election quite well, as do the Clinton voters in our sample compared to Clinton voters in the general election.

More specifically, an analysis of the voter data just after the election revealed that "in the 2016 election, a wide gap in presidential preferences emerged between those with and without a college degree. College graduates backed Clinton by a 9-point margin (52%-43%), while those without a college degree backed Trump 52%-44%"(Pew Research Center, November, 2016). In our data college graduates voted for Clinton in 51 % of the time while they voted Trump in 42 %. People without a college degree in our data voted for Clinton 41 % of the time compared to Trump with 57 %.

Moreover the analysis shows that "older voters (ages 65 and older) preferred Trump over Clinton 53%-45%."(Pew Research Center, November, 2016). In our data the numbers are 56%-42%.

In addition, women supported Clinton over Trump by 54% to 42% (Pew Research Center, November, 2016). In our data the margin is 49%-45%.

Further, young adults (18-25) preferred Clinton over Trump by a wide 55%-37% margin (Pew Research Center, November, 2016). In our data the margin is 52%-40%.

The analysis by the Pew Research Center (November, 2016) shows also that "Trump won whites with a college degree 49% to 45%" and he won won whites without a college degree 67% to 28%. In our data Trump won whites with a college degree 45% to 49% and he won won whites without a college degree 60% to 39%.

Thus, our selected sample shows a striking similarity to the general populations' patterns and reflects the attitudes of general Clinton and Trump voters rather reliably.

[30] Which in part might be explained by our selection of internet users.

4.2. Bidding behavior

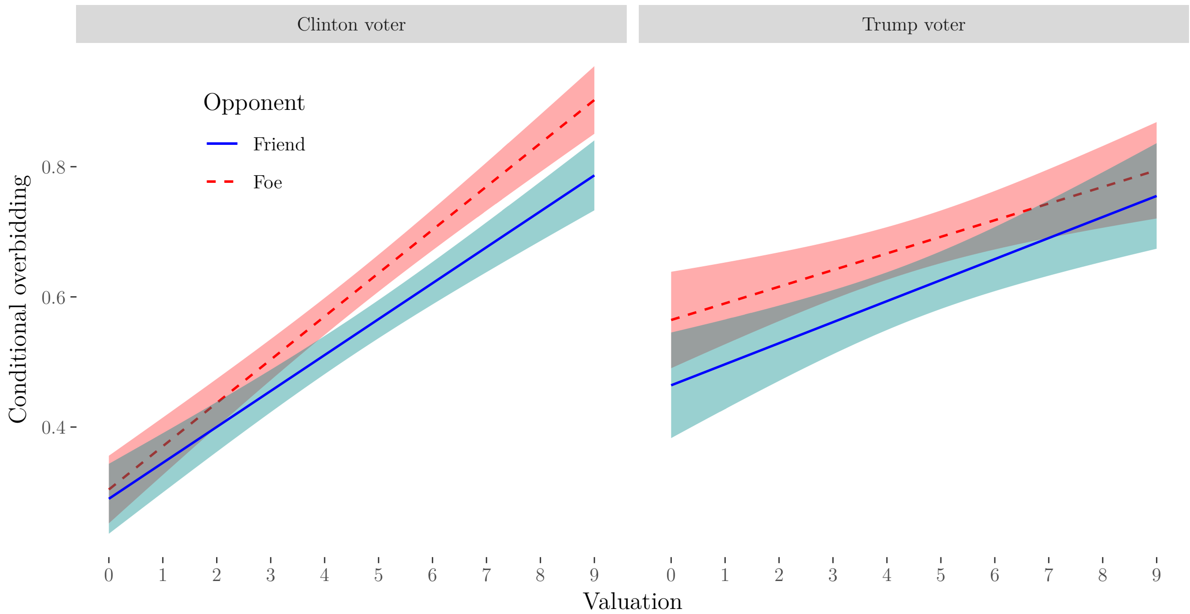


Figure 4: Conditional overbidding (actual bid minus risk neutral Nash-equilibrium bid) as a function of opponent and vote. Linear regression lines with confidence-interval-bands.

The left panel shows the overbidding behavior of Clinton voters. The right panel shows the overbidding behavior of Trump voters. Dashed, red lines depict the overbidding behavior if the opponent is a foe, i.e., the opponent voted not for the same candidate on election day. Solid, blue lines depict the overbidding behavior if the opponent is a friend, i.e., the opponent voted for the same candidate on election day.

Let us now consider subjects' bidding behavior. As our model predicts changes solely in the slope, we focus on the bidding behavior's functional form. Figure 4 shows conditional overbidding – defined as the difference between the actual bid and the risk-neutral Nash-equilibrium bid of a selfish bidder – as a function of the valuation. The graph on the left shows conditional overbidding for Clinton voters, while the graph on the right shows Trump voters' conditional overbidding. The red dashed line shows the regressed conditional overbidding if subjects were competing against foes (opposing voters). The solid blue line shows the regressed conditional overbidding if subjects were competing against friends (people who voted the same way).

It is apparent from Figure 4 that for Trump voters there is not much difference in behavior towards friends and foes. For Clinton voters, however, conditional overbidding seems to differ between friends and foes. To test for those effects, we estimate the bidding behavior.

As we used a strategy-method like approach, we control for the nested structure of the data by using a mixed effects model. Let us call $b_{i,v}$ the conditional bid of subject i conditional on the valuation v, with $i \in \{1, \ldots, 2616\}$ and $v \in \{0, \ldots, 9\}$. We use the following econometric model:

$$\begin{aligned} b_{i,v} =& \beta_1 + \beta_2 \cdot \mathbb{1}_{\text{Trump voters}} + \beta_3 \cdot \mathbb{1}_{Foe} + \beta_4 \cdot v + \beta_5 \cdot \mathbb{1}_{\text{Trump voters}} \cdot \mathbb{1}_{Foe} \\ &+ \beta_6 \cdot \mathbb{1}_{\text{Trump voters}} \cdot v + \beta_7 \cdot \mathbb{1}_{Foe} \cdot v + \beta_8 \cdot v \cdot \mathbb{1}_{\text{Trump voters}} \mathbb{1}_{Foe} \\ &+ \epsilon_i + v \cdot \epsilon_{i,v} + \epsilon^b_{i,j} \end{aligned} \tag{12}$$

where $b_{i,v}$ represents the bid of subject i for valuation v.[31] $\mathbb{1}_{Foe}$, denotes a dummy variable which is one if the subject competed against a foe and zero otherwise. $\mathbb{1}_{\text{Trump voters}}$, denotes a dummy with value one for Trump voters and zero otherwise. v is the private valuation of the auctioned object with $v \in \{0, \ldots, 9\}$. $\epsilon^b_{i,j}$ is the residual with $\epsilon^b_{i,j} \sim \mathcal{N}(0, \sigma^b)$. To account for the nested structure of the data we included ϵ_i as the random intercept effect of subject i and $\epsilon_{i,v}$ as the random slope effect of subject i resulting in a normal mixed effects model.

The estimated results of Equation 12 are shown in Table 2.

Firstly, we observe that subjects have a bidding intercept significantly different from zero (which might be explained by joy-of-winning). Further, we observe that subjects also have a slope significantly different from 0.50 (which could be risk-aversion). Interestingly, the conditional bidding of both Trump and Clinton voters towards friends is almost identical.[32] Further, we see that Trump and Clinton voters differ in their bidding for a valuation of zero as β_2 from Equation 12 (representing the estimated difference in bidding between both voter types towards friends for a valuation of zero) is significantly different from zero.

Most interestingly, however, it can be seen in Table 2 that β_8 (representing the estimated difference in conditional bidding between Trump and Clinton voters towards foes) is significantly smaller than zero, indicating that Trump voters had a less steep bidding function towards foes than Clinton voters. Thus, Trump voters have a less steep bidding function towards enemies than Clinton voters have towards enemies.

It is noteworthy, that while we randomly assigned an opponent (friend or foe) towards Trump and Clinton voters, we did not randomly assign who is a Trump and who is a Clinton voter. In Equation 12 we do compare the behavior of Trump and Clinton voters, and thus the results *might* be driven by subjects self-selecting into a Trump or Clinton voter. To control for potential biases, we use propensity score weighting by demographic characteristics in Appendix C.2. The results are qualitatively identical to the results reported here.[33]

Result 1.1. *Trump voters differ in their intercept, but display the same conditional bidding behavior towards friends as Clinton voters.*

Result 1.2. *Trump voters differ from Clinton voters significantly in their conditional bidding behavior towards enemies.*

[31] Note, that we do not separately estimate the overbidding behavior, as the risk neutral selfish Nash-equilibrium suggests a slop of .5 and an intercept of zero. Hence, the resulting estimates for overbidding would differ from the bidding behavior only in sofar as the slope-estimates would decrease by .5.

[32] β_7 from Equation 12 (representing the estimated difference in conditional bidding between both voter types towards friends) is not significantly different from zero. Moreover, $\beta_2^{(V)}$ from Equation 13 is 0.54 and 0.55 for Clinton and Trump voters respectively.

[33] We further, do not find any indication that the friends-foe-difference is varying with education.

Table 2: Mixed effects model estimates of Equation 12, e.g. the bidding behavior of Clinton voters and Trump voters.

	Bidding Behavior		
Constant	0.39^{***} (0.03)	0.31^{***} (0.03)	0.29^{***} (0.04)
Trump voters		0.20^{***} (0.05)	0.19^{**} (0.06)
Foe			0.04 (0.04)
V	0.55^{***} (0.01)	0.56^{***} (0.01)	0.54^{***} (0.01)
Foe x Trump voters			0.01 (0.07)
V x Trump voters		-0.03^{**} (0.01)	0.003 (0.01)
V x Foe			0.03^{***} (0.01)
V x Foe x Trump voters			-0.06^{***} (0.01)
Sbj.spe. intercept effects	✓	✓	✓
Sbj.spe. slope effects	✓	✓	✓
Observations	26,160	26,160	26,160
Log Likelihood	−30,870.52	−30,868.25	−30,844.99
Akaike Inf. Crit.	61,753.03	61,752.49	61,713.98
Bayesian Inf. Crit.	61,802.07	61,817.87	61,812.04

Notes: *p<0.05;**p<0.01;***p<0.001;

V denotes the valuation. *Foe* denotes a dummy with value one if the opponent is a foe (i.e., opponent voted not the same candidate on election day) and zero otherwise. *Trump voters* denotes a dummy with value one if the deciding subject is a Trump voter and zero if the deciding subject is a Clinton voter. Standard errors are in parenthesis. Heterogeneity on the subject level is accounted for by subject-specific random intercept and subject-specific random slope effects.

To make it easier for the reader to interpret our results we also estimate the bidding behavior separately for Trump voters and Clinton voters. For that we also use a mixed effects model:

$$\begin{aligned} b_{i,v} =& \beta_1^{(V)} + \beta_2^{(V)} \cdot \mathbb{1}_{Foe} + \beta_3^{(V)} \cdot v + \beta_4^{(V)} \cdot \mathbb{1}_{Foe} \cdot v + \epsilon_i + v \cdot \epsilon_{i,v} + \epsilon_{i,j}^{b} \\ &+ \underbrace{\Theta_1 \cdot X_k + \Theta_2 \cdot X_k \cdot v}_{\text{Controls}} \end{aligned} \quad (13)$$

$\mathbb{1}_{Foe}$, denotes a dummy variable which is one if the subject competed against a foe and zero otherwise. v is the private valuation of the auctioned object with $v \in \{0, \dots, 9\}$. X_k is a vector of control variables (such as Gender $\in$ {Male; Female}, Education $\in$ {College; No College}, Age $\in \{18, \dots, 88\}$, and reported Income $\in \{< 70.000, > 70.000\}$). $\epsilon_{i,j}^{b}$ is the residual, ϵ_i is the subject specific random intercept effect and $\epsilon_{i,v}$ as the random slope effect of subject i.

The estimation results of Equation 13 are shown in Table 3.[34]

[34] In Appendix C.4 we, in addition to the demographic controls, control for the income, unemployment, and poverty of the state the subject is living in, and we also control for the poverty and crime levels at the county level. The reported results are robust to all alternative specifications.

Table 3: Mixed effects model estimates of Equation 13.

	Bidding Behavior			
	Clinton voters		Trump voters	
Constant	0.28^{***} (0.04)	0.06 (0.11)	0.49^{***} (0.06)	0.44^{**} (0.17)
Foe	0.04 (0.04)	0.04 (0.04)	0.05 (0.06)	0.05 (0.06)
V	0.54^{***} (0.01)	0.62^{***} (0.02)	0.55^{***} (0.01)	0.60^{***} (0.03)
V x Foe	0.03^{***} (0.01)	0.03^{***} (0.01)	-0.03^{**} (0.01)	-0.03^{**} (0.01)
Sbj.spe. intercept effects	✓	✓	✓	✓
Sbj.spe. slope effects	✓	✓	✓	✓
Controls	×	✓	×	✓
Observations	16,210	16,210	9,950	9,950
Log Likelihood	−18,838.29	−18,850.87	−11,941.19	−11,958.70
Akaike Inf. Crit.	37,692.58	37,733.73	23,898.39	23,949.40
Bayesian Inf. Crit.	37,754.13	37,856.83	23,956.03	24,064.69

Notes: *p<0.05;**p<0.01;***p<0.001;
V denotes the valuation. *Foe* denotes a dummy with value one if the opponent is a foe (i.e., opponent voted not the same candidate on election day) and zero otherwise. *Trump voters* denotes a dummy with value one if the deciding subject is a Trump voter and zero if the deciding subject is a Clinton voter. Standard errors are in parenthesis. Heterogeneity on the subject level is accounted for by subject-specific random intercept and subject-specific random slope effects. Controls include the level and interaction effects of valuation with control variables (age, education, gender, income).

It is evident that the deductions from Figure 4 are partially supported by the econometric estimations: Clinton voters differentiate significantly between friends and foes (i.e., $\beta_4^{(V)}$ is significantly different from zero). Thus, Clinton voters have a steeper bidding function towards foes compared to friends. The behavior of Clinton voters is in line with the theory of spiteful bidding – bidders are theoretically expected to have an increase in their slope if they are spiteful (i.e., in competitions against foes compared to competitions against friends) but not in the intercept.

Trump voters show the exact opposite effect. While the Figure 4 does not show an obvious pattern for Trump voters, econometrically we see that Trump voters have a significantly less steep bidding function towards foes compared to friends ($\beta_4^{(V)}$ is significantly different from zero). This behavior is not well explained by the theoretical predictions of spiteful bidding.

All results are robust to controls (as can be seen from Table 3 Columns 2 and 4).

Result 2.1. *Trump voters do differentiate significantly in their bidding behavior between friends and foes – they bid less aggressively against foes than against friends.*

Result 2.2. *Clinton voters also significantly differentiate in their bidding behavior between friends and foes – they bid more aggressively (i.e., have a steeper bidding function) against foes than against friends.*

These findings are difficult to reconcile with standard models of auction behavior. Risk-aversion, anticipated regret, learning, joy-of winning all do not take preferences over the opponent into account. Thus, it seems like a model of social preferences might be useful to explain this behavior.[35] However, it also might be that not preferences are driving the effects but rather beliefs of the opponents' behavior.

[35] As mentioned in footnote 25 the results can equally be interpreted in terms of ingroup-outgroup behavior.

4.3. Beliefs

To examine whether beliefs and not preferences drive the effects, we elicit subjects beliefs about their opponent's bidding function in the third and fourth wave of the experiment (late October 2018 and early November 2018).[36] The conditional bidding beliefs are shown in Figure 5. The left panel shows the overbidding beliefs of Clinton voters while the right panel shows Trump voters overbidding beliefs. From visual inspection, it seems that Clinton voters expect friends as well enemies to deviate from the risk-neutral Nash-equilibrium in roughly the same way (same intercept and same slope). However, Trump voters seem to believe that Clinton voters will bid more aggressively (i.e., steeper slope) than fellow Trump voters.

To examine this relationship econometrically, we use the same model as in Equation 12 but estimate the bidding belief instead of the own bidding function. The resulting estimates are reported in Table 4. Similarly to the estimation of the bidding function, we also split the data into Trump and Clinton voters and estimate their beliefs in the same way as in Equation 13. The resulting estimates of the two subgroups are reported in Table 5.

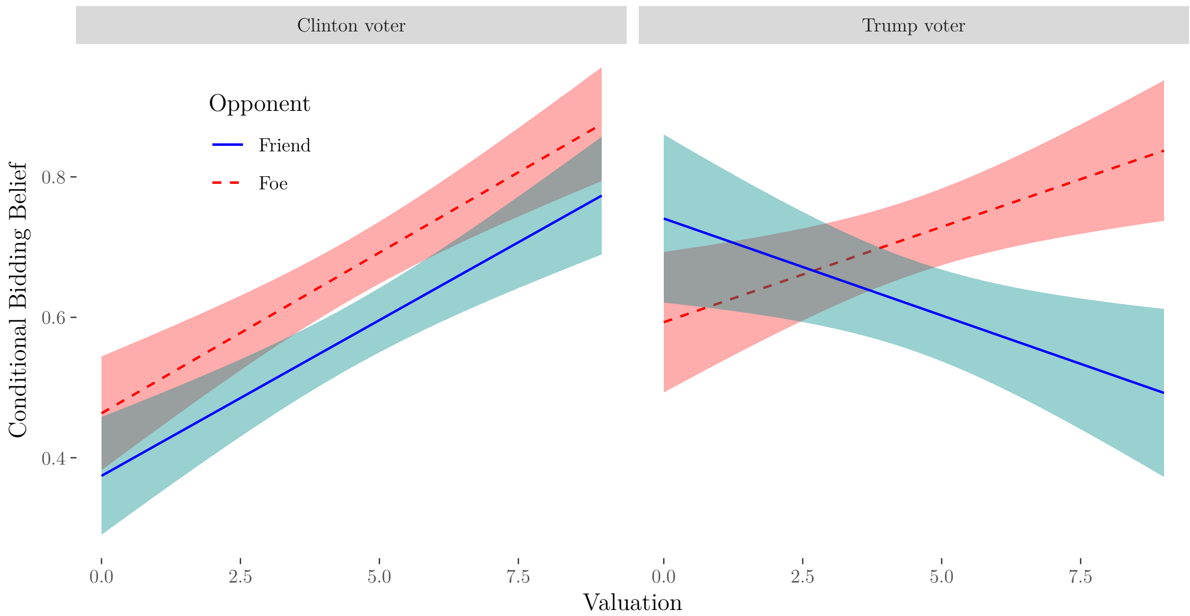


Figure 5: Conditional bidding beliefs as a function of opponent and vote. Linear regression lines with confidence-interval-bands.

The left panel shows the bidding beliefs of Clinton voters. The right panel shows the bidding beliefs of Trump voters. Dashed, red lines depict the bidding beliefs if the opponent is a foe, i.e., the opponent voted not for the same candidate on election day. Solid, blue lines depict the bidding beliefs if the opponent is a friend, i.e., the opponent voted for the same candidate on election day.

[36] See Appendix D.3 for the instructions.

Table 4: Mixed effects model estimates of Equation 12, e.g. the bidding beliefs of Clinton voters and Trump voters.

	Bidding Belief		
Constant	0.50*** (0.04)	0.41*** (0.05)	0.41*** (0.06)
Trump voters		0.21** (0.07)	0.18* (0.09)
Foe			0.01 (0.06)
V	0.53*** (0.01)	0.55*** (0.01)	0.55*** (0.01)
Foe x Trump voters			0.06 (0.09)
V x Trump voters		−0.05*** (0.01)	−0.08*** (0.02)
V x Foe			0.002 (0.01)
V x Foe x Trump voters			0.06*** (0.02)
Sbj.spe. intercept effects	✓	✓	✓
Sbj.spe. slope effects	✓	✓	✓
Observations	13,540	13,540	13,540
Log Likelihood	−14,996.69	−14,995.19	−14,967.95
Akaike Inf. Crit.	30,005.38	30,006.38	29,959.90
Bayesian Inf. Crit.	30,050.46	30,066.48	30,050.06

Notes: *p<0.05;**p<0.01;***p<0.001;

V denotes the valuation. *Foe* denotes a dummy with value one if the opponent is a foe (i.e., opponent voted not the same candidate on election day) and zero otherwise. *Trump voters* denotes a dummy with value one if the deciding subject is a Trump voter and zero if the deciding subject is a Clinton voter. Standard errors are in parenthesis. Heterogeneity on the subject level is accounted for by subject-specific random intercept and subject-specific random slope effects.

Table 5: Mixed effects model estimates of the bidding belief (Equation 13).

	Bidding Beliefs			
	Clinton voters		Trump voters	
Constant	0.40*** (0.05)	0.29 (0.16)	0.58*** (0.08)	0.61* (0.25)
Foe	0.01 (0.06)	0.01 (0.06)	0.10 (0.08)	0.10 (0.08)
V	0.54*** (0.01)	0.56*** (0.03)	0.48*** (0.01)	0.51*** (0.04)
V x Foe	0.004 (0.01)	0.004 (0.01)	0.06*** (0.01)	0.06*** (0.01)
Sbj.spe. intercept effects	✓	✓	✓	✓
Sbj.spe. slope effects	✓	✓	✓	✓
Controls	×	✓	×	✓
Observations	8,100	8,100	5,440	5,440
Log Likelihood	−8,657.54	−8,678.60	−6,268.78	−6,289.84
Akaike Inf. Crit.	17,331.09	17,389.20	12,553.56	12,611.68
Bayesian Inf. Crit.	17,387.08	17,501.19	12,606.37	12,717.31

Notes: *p<0.05;**p<0.01;***p<0.001;

V denotes the valuation. *Foe* denotes a dummy with value one if the opponent is a foe (i.e., opponent voted not the same candidate on election day) and zero otherwise. Standard errors are in parenthesis. Heterogeneity on the subject level is accounted for by subject-specific random intercept and subject-specific random slope effects. Controls include the level and interaction effects of valuation with control variables (age, education, gender, income).

It is evident from the estimation that the visual inspections were correct. Clinton voters believe their opponent to bid roughly the same independent of whether the opponent is a friend or a foe (i.e., *V x Foe* and *Foe* are not significantly different from zero). Trump voters, however, believe that foes (Clinton voters) will have a steeper bidding function compared to friends (i.e., *V x Foe* is significantly different from zero). Similarly, it is evident from Table 4 that Clinton and Trump voters differ in their beliefs.

These results suggest that beliefs cannot account for the whole change in behavior. Clinton voters do not expect their opponent to differ from their friend. At the same time, they bid more aggressively towards enemies compared to friends. Thus, beliefs cannot explain this behavior for Clinton voters.

Trump voters, on the other hand, belief Clinton voters to bid more aggressively towards them. This theoretically would result in a lower bidding slope. This, in turn, might explain why the conditional bidding slope of Trump voters is smaller towards enemies compared to friends.

Result 3.1. *Trump and Clinton voters differ in their belief of the opponent's bidding function.*

Result 3.2. *Clinton voters belief their opponent to bid the same independent of whether the opponent is a friend or a foe.*

Result 3.3. *Trump voters belief that foes will have a steeper bidding function than friends.*

Next, we want to see whether the bidding behavior is still influenced by the opponent if accounted for beliefs. To do so, we estimate Equation 13 with the addition of a fixed effect for the bidding belief of subject i, i.e., the average bidding belief.[37] The resulting estimates are reported in Table 6. We see again that Clinton voters have a steeper bidding function towards enemies even if we account for beliefs. Similarly, Trump voters have a less steep bidding function towards enemies even if we account for beliefs (however, the effect is not significant anymore). Thus, the effect reported in Table 3 prevails in most part if we account for subjects' beliefs.

Table 6: Mixed effects model estimates of Equation 13, i.e., the conditional bidding behavior, while accounting for beliefs.

	Bidding Behavior					
	Clinton voters			Trump voters		
Constant	0.28*** (0.04)	−1.34*** (0.07)	−1.58*** (0.16)	0.49*** (0.06)	−1.43*** (0.09)	−1.50*** (0.22)
Belief		0.60*** (0.02)	0.60*** (0.02)		0.69*** (0.02)	0.69*** (0.02)
Foe	0.04 (0.04)	−0.06 (0.06)	−0.06 (0.06)	0.05 (0.06)	0.01 (0.08)	0.01 (0.08)
V	0.54*** (0.01)	0.52*** (0.01)	0.59*** (0.03)	0.55*** (0.01)	0.52*** (0.01)	0.55*** (0.04)
V x Foe	0.03*** (0.01)	0.06*** (0.01)	0.06*** (0.01)	−0.03** (0.01)	−0.01 (0.02)	−0.01 (0.02)
Sbj.spe. intercept effects	✓	✓	✓	✓	✓	✓
Sbj.spe. slope effects	✓	✓	✓	✓	✓	✓
Controls	×	×	✓	×	×	✓
Observations	16,210	8,100	8,100	9,950	5,440	5,440
Log Likelihood	−18,838.29	−8,757.14	−8,776.98	−11,941.19	−6,412.06	−6,431.74
Akaike Inf. Crit.	37,692.58	17,532.27	17,587.95	23,898.39	12,842.12	12,897.48
Bayesian Inf. Crit.	37,754.13	17,595.27	17,706.95	23,956.03	12,901.53	13,009.70

Notes: *p<0.05;**p<0.01;***p<0.001;
V denotes the valuation. *Foe* denotes a dummy with value one if the opponent is a foe (i.e., opponent voted not the same candidate on election day) and zero otherwise. *Belief* denotes what the subject beliefs his opponent will bid on average. Standard errors are in parenthesis. Heterogeneity on the subject level is accounted for by subject-specific random intercept and subject-specific random slope effects. Controls include the level and interaction effects of valuation with control variables (age, education, gender, income).Columns 2, 3, 5, and 6 control for the belief of the bidding subject while columns 1 and 4 just replicate the findings from Table 3. As we elicit beliefs only in the third and fourth wave, the observations in columns 2, 3, 5, and 6 are smaller than in columns 1 and 4.

4.4. Conditional bidding as a function of attitudes towards opponents

Next, we want to provide further support that attitudes and preferences over the opponent drive the behavior. To do so, we want to use the subjects' attitudes towards their opponent.

As part of the post-experimental questionnaire we assessed which attitudes subjects had towards their foes and towards their friends by using the social distance questionnaire and the feeling thermometer.

[37] As the valuation for the opponent is drawn independently from the own valuation, we need to account for the expected bid.

To see whether the attitudes towards the respective player was influencing the bidding behavior we estimate the same model as in Equation 13, while we replace the $\mathbb{1}_{Foe}$ dummy by the social closeness measure (*SocialCloseness*), or feeling thermometer (*FeelWarmth*), respectively. Increasing values of *FeelWarmth* indicate that subjects feel *warmer* about the person in question and thus have better attitudes towards that person. Similarly, increasing values of *SocialCloseness* indicate that subjects feel *closer* towards the person in question and therefore have better attitudes towards that person. To keep the results comparable, we standardize both measures of attitudes.

Table 7 shows the estimation. It can be seen that the conditional bidding behavior is influenced by the attitudes towards the opponent exactly the same way as the conditional bidding was influenced by the type (friend or foe) of the opponent - increasingly positive attitudes decreased the bidding slope. Or put differently: the worse the attitude towards the opponent the higher the bidding slope. However, this relationship is true only Clinton voters. Trump voters are either not or conversely affected in their bidding behavior by their attitudes towards the opponent.

Table 7: Mixed effects model of the conditional bidding as a function of how warm subjects felt towards their opponent, and how close subjects felt towards their opponent.

	Bidding Behavior			
	Trump voters		Clinton voters	
Constant	0.54^{***} (0.05)	0.52^{***} (0.05)	0.31^{***} (0.03)	0.30^{***} (0.03)
V	0.53^{***} (0.01)	0.53^{***} (0.01)	0.56^{***} (0.01)	0.56^{***} (0.01)
SocialCloseness	-0.11^{***} (0.03)		0.02 (0.02)	
V x SocialCloseness	0.01 (0.01)		-0.02^{***} (0.004)	
FeelWarmth		-0.02 (0.03)		-0.01 (0.02)
V x FeelWarmth		0.01^{*} (0.01)		-0.02^{***} (0.004)
Sbj.spe. intercept effects	✓	✓	✓	✓
Sbj.spe. slope effects	✓	✓	✓	✓
Observations	9,950	9,950	16,210	16,210
Log Likelihood	−11,940.91	−11,944.07	−18,853.34	−18,846.86
Akaike Inf. Crit.	23,897.82	23,904.13	37,722.69	37,709.72
Bayesian Inf. Crit.	23,955.46	23,961.77	37,784.24	37,771.27

Notes: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$;

Increasing values of *FeelWarmth* indicate that subjects feel *warmer* about the person in question and increasing values of *SocialCloseness* indicate that subjects feel *closer* towards the person in question. Standard errors are in parenthesis. Heterogeneity on the subject level is accounted for by subject-specific random intercept and subject-specific random slope effects. Both measures of attitudes are standardized.

Result 4.1. *The worse the attitude towards the opponent the higher the bidding slope of Clinton voters.*

Result 4.2. *Trump voters are not or conversely affected in their bidding behavior by their attitudes towards the opponent.*

4.5. Summary and discussion

In summary, we have seen that the competitor matters. Clinton and Trump voters show almost an identical bidding slope towards friends. Towards foes, Trump voters have a less step bidding slope. Clinton voters exhibit a significantly steeper bidding slope towards Trump voters compared to Clinton voters. These effects persist even if we account for the bidding beliefs of Clinton and Trump voters. We further saw that these behavioral patterns are strongly correlated with the personal attitudes subjects had towards their opponent. In particular, we saw that Clinton voters exhibit a less steep bidding function with increasing empathy towards the opponent, while this was not (or reversely) found for Trump voters.

Thus, we have seen that the role of the competitor does influence both Clinton and Trump voters. Taking the opponent into account in fact also leads to a reduced expected payoff for participants. Comparing the expected empirical payoff[38] of Clinton voters who are either competing against a fellow Clinton voter or a Trump voter we find that, on average, the payoff is significantly smaller for Clinton voters, if they compete against Trump voters compared to fellow Clinton voters (Wilcoxon W= 369329.5, p<0.001). More specifically, it results in a 6% smaller payoff for Clinton voters if they compete against a foe compared to a fellow Clinton voter. For Trump voters, the payoff is 5% smaller if they compete against a Clinton voter compared to a fellow Trump voter, which, is significantly different from zero (Wilcoxon W= 132456, p= 0.014). This effect is driven by 1) Clinton voters bidding more against Trump voters, and by 2) Trump voters bidding less against Clinton voters, which results overall in a smaller probability of winning for Trump voters who compete against Clinton voters. Overall, this results in a situation where subjects obtain on average a 6% smaller payoff if they play the auction against a non-partisan compared to a partisan.

It is noteworthy that the observed behavior is hard to reconcile with standard explanations like risk-aversion, joy-of winning, anticipated regret, or learning. As our experiment consists of only a single shot situation, learning is impossible. Further, joy-of winning – i.e., assuming that subjects obtain an additional payoff for just winning – cannot explain our results, as this motive does not hinge on the opponent's type. The same is true for anticipated regret, which also does not depend on the opponent. To the same extent, risk-aversion cannot explain our findings as risk aversion predicts a steeper bidding slope, but this prediction is independent of the opponent. Only, a theory which takes the opponent into account can explain our results. One such possible set of theories are social preferences. Building on the model by Morgan et al. (2003), we show that spiteful bidding would nicely explain the behavior of Clinton voters, as the theory also predicts a steeper bidding slope if a subject is increasingly spiteful. Identical predictions can be obtained using ingroup-outgroup preferences (Klor and Shayo, 2010), and thus, our results can also be interpreted as evidence of outgroup-hate influencing bidding behavior.[39]

[38] We empirically estimate the winning probability (in each given treatment) for a given valuation for a given subject and calculate the expected payoff $(p(winning) * (b - v))$ for each subject.

[39] However, it is noteworthy that neither ingroup-outgroup preferences nor spiteful preferences can explain the heterogeneous differential effects between Clinton and Trump voters. Thus, we can only partially confirm the theory of spiteful preferences influencing bidding behavior as the results hold only for a subgroup (i.e., Clinton voters). While providing a theory explaining the heterogeneous effects between Clinton and Trump voters would be very valuable, this would 1) exceed the scope of the paper and 2) require more information

Our results provide important evidence, that partisanship can even influence behavior on a market place. This behavior imposes externalities on the whole market, as bidders are bidding more to harm the competitor. Extrapolating from our results, one might conclude that partisanship can also lead to higher expenses in other kinds of interactions between Democrats and Republicans: from lobbying to election campaigning - Democrats might be overinvesting, in part, to harm Republicans.

However, one of the main questions resulting from this work is why do we find the effect for Clinton voters, however not for Trump voters. One possible explanation might be that Clinton voters feel morally superior over Trump voters, and this, in turn, results in more aggressive behavior. This argument would be very much in line with psychological literature suggesting that moral superiority leads to outgroup hate (see e.g.: Brewer, 1999; Mummendey and Wenzel, 1999; Parker and Janoff-Bulman, 2013). Similarly, recent polls indicate that a majority of Democrats indicate to feel angry going into the midterm elections of 2018 while only 30 percent of Republicans say the same.[40] In Appendix C.3 we also discuss whether and how morality differs between Clinton and Trump voters. However, further work needs to investigate whether this difference in behavior between Clinton and Trump voters is really caused by perceived moral superiority or by another phenomenon.

There are also several limitations of this work worth to be pointed out. First, while we compare how the opponents' partisanship impact the bidding behavior, we do not compare our results to a neutral baseline. Thus, we, for example, cannot say whether Clinton voters bid more aggressively towards Trump voters relative to a neutral baseline or whether Clinton voters bid less aggressive towards fellow Clinton voters relative to a neutral baseline. While such a comparison might be interesting, it would not primarily contribute to our research question, i.e., partisanship spills over into market interactions in the form of first-price auctions. Thus, while we could have made slightly more nuanced comments on how partisanship affects market interactions, we mainly wanted to establish whether such a link exists at all.

Second, the paper does not have an exogenous 2x2 design, as we did not randomly assign the partisanship towards subjects. Thus, participants endogenously choose their partisanship, which might result in possible confounds. It might, for example, be that education is confounded with our results. However, 1) the friends-foe-difference does not vary with education, 2) the opponent *is* randomly assigned towards subjects and 3) all our results are robust towards using propensity score matching. Thus, it is unlikely that better-educated subjects drive the results.[41] However, it might be that participants bid towards a less educated person more aggressively, and education does correlate with partisanship. Even though this concern is very valid there are two comments on this issue: 1) the education of the opponent should not matter for the bid of the subject (in fact if one would assume a less educated person to play randomly the optimal behavior is still to bid half the valuation) and 2) demographic characteristics are inherently

on what exactly is driving these heterogeneous differences. We hope that future research will be able to speak to this question.

[40] See https://www.politico.com/story/2018/11/05/poll-generic-ballot-narrows-on-eve-of-midterms-960757.

[41] Similar arguments hold for gender, age, income etc, as the results are robust towards using propensity score matching.

different between voters and thus, to study our research question (i.e., whether partisanship spills over into the market) we need the variation in demographic characteristics.[42] Thus, while we cannot say which of the opponents' attributes are driving exactly the behavior – it might be just education, it might be the mix of age, and education or it might be the full set of attributes constituting a Clinton/Trump voter – we can say that preferences over the opponent (consolidated in the opponents' partisanship) are influencing the bidding decision of subjects.

All in all, this paper provides first experimental evidence for social preferences, in the form of partisanship, influencing behavior in auctions, in particular the first-price winner-pay auction, as the opponent's type (friend vs. foe) is relevant for bidding behavior. This constitutes the main contribution of the paper: preferences over other bidders impact the strategic decision on bidding. Further, our paper provides evidence that partisanship can spill over even into market interactions.

Taking this insight into account might be relevant to design mechanism robust to social preferences and robust to whether the opponent is a friend or an enemy. Bartling and Netzer (2016), Bierbrauer and Netzer (2016) and Bierbrauer et al. (2017) go into that direction and already provide externality-robust mechanisms to cope with potential social preferences influencing behavior in market interactions. In particular, Bartling and Netzer (2016) provide an auction mechanism robust to social preferences. Our paper highlights the importance of such mechanisms, as standard mechanisms are prone to welfare-losses (on the consumer side) due to social preferences, as this paper shows.

5. Conclusion

In this paper, we report on competitions, in form of first-price auctions, between Clinton and Trump voters. Using a model of spiteful bidding, we predict that participants will have a steeper bidding function against opposing voters compared to coinciding voters. We show that Clinton voters indeed bid more aggressively if the competitor is a Trump voter compared to a fellow Clinton voter as competitor. This is not the case of Trump voters. We further show that these effects prevail even if we account for bidding beliefs. However, measures of empathy were strongly predictive of the bidding behavior of Clinton voters, in line with the theory of spiteful bidding. We show that this behavior results in a 6% lower income for participants who compete against opposing voters compared to coinciding voters. Overall, this paper provides first experimental evidence for social preferences influencing behavior in auctions and provides further evidence, that partisanship can spill over even into market interactions.

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[42] One possible way around this issue is to ask all subjects to compete, for example, with a white female between 25 and 30 having a bachelors' degree while just varying the vote of that female. While this might be feasible, this approach would result in deception if we cannot ensure such a matching.

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Appendix (for online publication)

A. The sample

In subsection A.1 we give a very brief overview of Amazon's Mechanical Turk (MTurk) to readers unfamiliar with MTurk. In subsection A.2 we show how coherent our sample made decisions. In particular, we show consistency in decisions and performance on attention checks.

A.1. Amazon's Mechanical Turk

Amazon's Mechanical Turk is an online labor market and frequently used by social scientists for experiments[43].

Workers in MTurk can choose among Human intelligence tasks (HITs), and they will be paid by the requester after performing the task. These tasks are relatively simple and are relatively quick. Common tasks are answering surveys, transcribing data, classifying images, transcribing audio clips, translation rating etc. (Berinsky et al., 2012; Horton et al., 2011; Mason and Suri, 2012; Paolacci et al., 2010).

MTurk samples tend to be more representative of the U.S. population than typical samples (Berinsky et al., 2012; Buhrmester et al., 2011; Paolacci et al., 2010), and samples are usually more diverse in age, ethnicity, education and geographical location than students (Berinsky et al., 2012; Buhrmester et al., 2011; Paolacci et al., 2010). Most importantly, however, is that the data obtained in MTurk is at least as reliable as those obtained via traditional methods (Berinsky et al., 2012; Buhrmester et al., 2011; Horton et al., 2011; Paolacci et al., 2010), while subjects are paid significantly less in MTurk (Buhrmester et al., 2011).

Only US-based workers, verified through IP addresses in MTurk, with an average approval rate of 97%[44] and an approved amount of tasks of no less than 500 were allowed to take part in our experiment.[45]

A.2. Coherence

To ensure that subjects are not randomly choosing a candidate and are really paying attention we asked subjects also for their preferred political party and we included several attention checks.

A.2.1. Consistency

We asked subjects in the general demographics part "With which party do you normally identify yourself most with?" and later in the study, we asked "Which political party do you usually

[43] For example : Chen and Horton (2010), Horton et al. (2011), Jordan et al. (2017), Jordan et al. (2016), Mao et al. (2017), Peysakhovich et al. (2014), Rand et al. (2014), and Suri and Watts (2011). See Arechar et al. (2018) for a comparison between lab and online experiments, indicating that the results obtain from MTurk-experiments are very similar to the ones made in the lab.

[44] Requesters can review the work done by MTurkers and decide to approve or reject the work. Approved work is paid as indicated in the contract and rejected work is not paid. Hence, higher approval rates of workers indicate a higher quality of work.

[45] Participants were told that they would be paid within one week. After finishing collection, we matched subjects according to the instructions and paid them their bonus. Bonus payment was automated and implemented via AMS and R.

feel closest to".

99.5 % of those subjects who indicated to identify most with democrats also felt closest to democrats, and similarly 99.1 % of those subjects who indicated to identify most with republicans also felt closest to republicans.

Furthermore, 91.5 % of those subjects who indicated to have voted for Hillary Clinton also felt closest to the democrats, and similarly 85.1 % of those subjects who indicated to have voted for Donald Trump also felt closest to the republicans.

Additionally, 77.5 % of those subjects who indicated to have voted for Hillary Clinton are normally identifying themselves with democrats (6.1 % normally identify themselves with independents), and similarly 69.4 % of those subjects who indicated to have voted for Donald Trump normally identify themselves with the republicans (24.4 % normally identify themselves with independents).

A.2.2. Attention Checks

In some of the questionnaires we included additional attention checks by asking questions for example "Click on agree" or "This is another control. We ask you to select the second option." We included four of those attention checks (without having any impact on the participants). Only 2 % of all subjects failed one or more of those attention checks (some of the subjects, however, reported to have misunderstood the meaning of "second option" as this might have been ambiguous in regard to the reference point).

Overall, the quality of the data seems to be very good.

B. Measures of Attitude

In the post-experimental questions we elicited, among other things, attitudes towards the opponent by utilizing the social distance questionnaire and the feeling thermometer which both will be discussed in more detail in section B.1 and B.2.

B.1. Social distance questionnaire

The social distance questionnaire is designed "to measure social rejection and willingness to interact with an individual member of a social group"(Robinson et al., 1999, p. 341 ff). In our experiment the respective social groups where Trump voters and Clinton voters. This questionnaire elicits the agreeableness upon 7 items on a scale between 1 and 7, were subjects were asked to rate how strongly they agree with the following example statements of a person who is a Clinton or Trump voter "This appears to be a likable person" or "I would like this person to move into my neighborhood". Higher scores indicate feeling closer to the individual member of the respective social group.

B.2. Feeling Thermometer

The feeling thermometer is commonly used in polling (f.e. American national election studies), political sciences (Greene, 1999; Kaid et al., 1992; Miller and Wlezien, 1993) and also in medicine

(Jacobson et al., 1992; Patrick et al., 1994; Schünemann et al., 2003). The feeling thermometer asks subjects to imply how warm they feel towards a specific group or person. We asked subject to indicate their feeling towards Clinton voters, Trump voters, Republicans in general and Democrats in general, on a scale between 0 and 10. Subjects were told that if they had a positive feeling toward a group or feel favorably towards it, they should give it a score somewhere between 5 and 10, depending on their feeling. If they felt negatively they should give a score between 0 and 5 and in case of no feeling they should give a score of 5.

C. Further regressions

C.1. Summary statistics

Table 8 shows summary statistics of the main variables by vote.

Table 8: Summary statistics of the main variables by vote.

Test	Clinton voters ($N = 1621$)	Trump voters ($N = 995$)	T	Df	p	95% CI	Sign.
Bid	2.82	2.89	-1.57	2614.00	0.12	[-0.15 , 0.02]	
Belief	2.85	2.89	-0.71	1352.00	0.47	[-0.17 , 0.08]	
△ SocialCloseness	2.59	1.81	12.24	2614.00	0.00	[0.66 , 0.91]	$***$
△ FeelWarmth	6.06	5.08	8.50	2614.00	0.00	[0.75 , 1.2]	$***$
Moral	3.68	4.09	-4.48	1352.00	0.00	[-0.6 , -0.23]	$***$
We use two sample t-tests to compare characteristics						*p<0.05;**p<0.01;***p<0.001;	

Bid denotes the average bid. *Belief* denotes the average bidding belief. △ *SocialCloseness* denotes the difference in social closeness between friends and opponents. Higher values indicate a larger gap in the social closeness between friends and opponents. △ *FeelWarmth* denotes the difference in the feeling of warmth between friends and opponents. Higher values indicate a larger gap in the feeling of warmth between friends and opponents. *Moral* denotes the perception of the morality of the opponent.

C.2. Propensity score matching

Even though subjects were assigned an opponent randomly, subjects did select whether to be a Trump or a Clinton voter. Throughout most of the paper we only compare the behavior towards an opponent within a group (either Trump or Clinton voters) but in Equation 12 we also compare whether Clinton and Trump voters differ in their bidding behavior. To control for self-selection we use nearest neighbor propensity score matching to estimate Equation 12. More specifically, we match subjects on the following demographic characteristics: Age, gender, education, ethnicity, and income. Table 9 shows the estimation of Equation 12 using propensity score matching. It is evident from Table 9 that all results are qualitatively not influenced by subjects self-selecting into Clinton and Trump voters.

Table 9: Mixed effects model estimates of Equation 12 using nearest neighbor propensity score matching.

		Bidding Behavior	
Constant	0.39^{***} (0.03)	0.30^{***} (0.03)	0.26^{***} (0.04)
Trump voters		0.21^{***} (0.05)	0.23^{***} (0.06)
Foe			0.09^{*} (0.04)
V	0.55^{***} (0.01)	0.56^{***} (0.01)	0.54^{***} (0.01)
Foe x Trump voters			−0.04 (0.07)
V x Trump voters		-0.02^{*} (0.01)	0.01 (0.01)
V x Foe			0.04^{***} (0.01)
V x Foe x Trump voters			-0.07^{***} (0.01)
Sbj.spe. intercept effects	✓	✓	✓
Sbj.spe. slope effects	✓	✓	✓
Observations	26,160	26,160	26,160
Log Likelihood	−33,818.19	−33,815.11	−33,768.78
Akaike Inf. Crit.	67,648.37	67,646.22	67,561.56
Bayesian Inf. Crit.	67,697.40	67,711.59	67,659.62

Notes: *p<0.05;**p<0.01;***p<0.001;

V denotes the valuation. *Foe* denotes a dummy with value one if the opponent is a foe (i.e., opponent voted not the same candidate on election day) and zero otherwise. *Trump voters* denotes a dummy with value one if the deciding subject is a Trump voter and zero if the deciding subject is a Clinton voter. Standard errors are in parenthesis. Heterogeneity on the subject level is accounted for by subject-specific random intercept and subject-specific random slope effects.

C.3. Moral attitudes

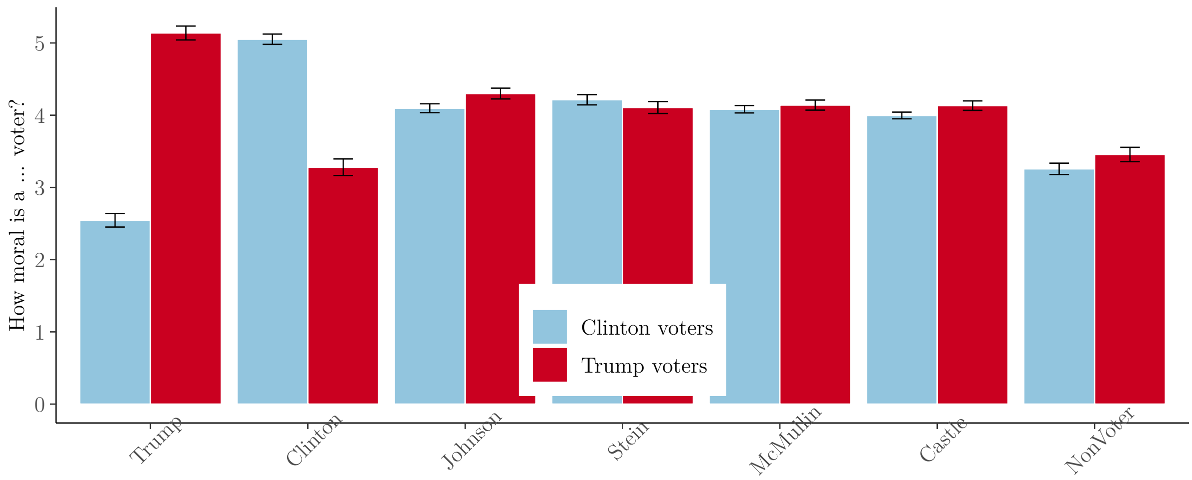

Figure 6: How moral subjects report to consider different voters (means with 95% confidence intervals).

To further investigate whether the perception of morality might drive the difference between Clinton and Trump voters we elicit their moral attitudes during the third and fourth wave of the experiment (late October 2018 and early November 2018). In particular, we asked participants how moral they consider a Trump, Clinton, Johnson, Stein, McMullin, and Castle voter as well as people who did not vote during the presidential election 2016. The results are shown in Figure 6.

The moral attitudes of both Clinton and Trump voters are very similar and rather neutral for

Johnson, Stein, McMullin, and Castle voters. Both Clinton and Trump voters considered non-voters significantly less moral than Johnson, Stein, McMullin, and Castle voters.[46] Interestingly, Clinton voters considered Clinton voters as moral as Trump voters considered Trump voters[47], which was significantly better than Johnson, Stein, McMullin, and Castle voters ($t(1353)=$ -27.3, $p<0.001$).

More importantly, we can see that Trump voters considered Clinton voters significantly less moral than fellow Trump voters[48], than Johnson, Stein, McMullin, Castle voters[49] and even less than non-voters[50].

The same pattern can be found for Clinton voters who considered Trump voters significantly less moral than fellow Clinton voters[51], than Johnson, Stein, McMullin, Castle voters[52] and even less than non-voters[53]. Even more interestingly, the difference in morality between friends and foes is much more pronounced for Clinton voters, who considered Trump voters significantly less moral than Trump voters considered Clinton voters.[54]

Using this insight, we can also try to predict the bidding behavior using the attitudes on morality. To see whether the moral attitudes towards the respective opponent was influencing the bidding behavior we estimate the same model as in Equation 13, while we replace the $\mathbb{1}_{Foe}$ dummy by the moral attitude toward the opponent. Increasing values of *moral* indicate that subjects consider their opponent more moral.

Table 10 shows the estimation. It can be seen that the conditional bidding behavior is influenced by the attitudes towards the opponent exactly the same way as the conditional bidding was influenced by the type (friend or foe) of the opponent - increasingly positive attitudes decreased the bidding slope. Or put differently: the worse the attitude towards the opponent the higher the bidding slope. However, this relationship is true only Clinton voters. Trump voters are conversely affected in their bidding behavior by their attitudes towards the opponent.

[46] In particular, non-voters were considered to be $M = 3.34$ points moral on a scale from one to seven while Johnson, Stein, McMullin, and Castle voters were considered on average to be $M = 4.13$ points moral on a scale from one to seven, a highly significant difference ($t(1353)=$ 21.5, $p<0.001$).

[47] In particular, Clinton voters considered fellow Clinton voters to be $M = 5.05$ points moral on a scale from one to seven while Trump voters considered fellow Trump voters to be $M = 5.14$ points moral on a scale from one to seven, $t(1083.1)=$ -1.4, $p>0.05$.

[48] In particular, Trump voters considered fellow Trump voters to be $M = 5.14$ points moral on a scale from one to seven while Clinton voters were considered to be $M = 3.28$ points moral on a scale from one to seven, a highly significant difference $t(543)=$ 22.1, $p<0.001$.

[49] In particular, Trump voters considered Johnson, Stein, McMullin, Castle on average to be $M = 4.17$ points moral on a scale from one to seven while Clinton voters were considered to be $M = 3.28$ points moral on a scale from one to seven, a highly significant difference $t(543)=$ 13.3, $p<0.001$.

[50] In particular, Trump voters considered non-voters on average to be $M = 3.46$ points moral on a scale from one to seven while Clinton voters were considered to be $M = 3.28$ points moral on a scale from one to seven, a highly significant difference $t(543)=$ -2.7, $p=$ 0.008.

[51] In particular, Clinton voters considered fellow Clinton voters to be $M = 5.05$ points moral on a scale from one to seven while Trump voters were considered to be $M = 2.55$ points moral on a scale from one to seven, a highly significant difference $t(809)=$ -36.9, $p<0.001$.

[52] In particular, Clinton voters considered Johnson, Stein, McMullin, Castle on average to be $M = 4.10$ points moral on a scale from one to seven while Trump voters were considered to be $M = 2.55$ points moral on a scale from one to seven, a highly significant difference $t(809)=$ 29, $p<0.001$.

[53] In particular, Clinton voters considered non-voters on average to be $M = 3.26$ points moral on a scale from one to seven while Clinton voters were considered to be $M = 2.55$ points moral on a scale from one to seven, a highly significant difference $t(809)=$ -13.8, $p<0.001$.

[54] In particular, Clinton voters considered Trump voters to be $M = 2.55$ points moral on a scale from one to seven while Trump voters considered Clinton voters to be $M = 3.28$ points moral on a scale from one to seven, a highly significant difference $t(1165.1)=$ -9.7, $p<0.001$.

Table 10: Mixed effects model of the conditional bidding as a function of moral subjects considered their opponent.

	Bidding Behavior		
	All	Trump voters	Clinton voters
Constant	0.50*** (0.07)	0.95*** (0.13)	0.27*** (0.08)
V	0.56*** (0.01)	0.46*** (0.02)	0.62*** (0.02)
Moral	−0.02 (0.02)	−0.09** (0.03)	0.02 (0.02)
V x Moral	−0.01* (0.003)	0.01** (0.005)	−0.02*** (0.003)
Sbj.spe. intercept effects	✓	✓	✓
Sbj.spe. slope effects	✓	✓	✓
Observations	13,540	5,440	8,100
Log Likelihood	−16,071.23	−6,727.96	−9,299.24
Akaike Inf. Crit.	32,158.46	13,471.91	18,614.48
Bayesian Inf. Crit.	32,218.57	13,524.72	18,670.47

Notes: *p<0.05;**p<0.01;***p<0.001;

Increasing values of *Moral* indicate that subjects consider the person in question more moral. Standard errors are in parenthesis. Heterogeneity on the subject level is accounted for by subject-specific random intercept and subject-specific random slope effects.

Result 5.1. *Clinton and Trump voters considered non-voters less moral than Johnson, Stein, McMullin, and Castle voters and they consider fellow voters most moral.*

Result 5.2. *Clinton and Trump voters considered opposing voters (i.e., Trump and Clinton voters respectively) as least moral, while Clinton voters consider Trump voters significantly less moral than Trump voters considered Clinton voters.*

Result 5.3. *The worse the attitude towards the opponent the higher the bidding slope of Clinton voters.*

Result 5.4. *Trump voters are conversely affected in their bidding behavior by their attitudes towards the opponent.*

C.4. Further controls

To ensure robustness of our results we extend in this section the estimation of Section 4 to further controls.

For that purpose we extend the vector of controls X_k from Equation 13 by further controls, we were able to derive by having approximate locations of the subjects taking part in the study.[55] We matched subjects' locations with governmental data on poverty and crime of the subjects' county and poverty, income and unemployment of the subjects' state.

The data on poverty on the county level was obtained from United States Department of Agriculture[56] and the data on the state level was gathered from the United States Census

[55]Using Qualtrics enabled us to collect data on the current whereabouts of almost all the participating subjects (the location of 12 subjects was not reported). However, the location is accurate roughly at a city-level.

[56]The data can be found here: https://www.ers.usda.gov/data-products/county-level-data-sets/county-level-data-sets-download-data/ (United States Department of Agriculture, 2017). The poverty estimates reported in this data are model estimates from the U.S. Census Bureau's Small Area Income and Poverty Estimate.

Bureau[57]. To control for poverty on the county level we included the poverty as reported in United States Department of Agriculture (2017). We also controlled for the percentage of people living below the poverty level on the state level from the Census Data. Also from the Census Data (state level), we obtained the median income and the percentage of unemployment.

The crime data was obtained from the "Uniform Crime Reporting Program Data: County-Level Detailed Arrest and Offense Data, 2014" reported by the United States Department of Justice, Federal Bureau of Investigation[58]. To control for crime in the county of the participating subject, we include the relative crime (amount of reported crimes relative to the population of the county) and the relative violent crime (amount of reported violent crimes relative to the population of the county).

Table 11 shows the estimations. It is evident, that results are robust to these controls.

C.5. Structural estimation of α

Given our results we can structurally estimate the spitefulness subjects experience. To get the spite parameter we estimate the following model:[59]

$$b_{i,v} = \beta_1^{(S)} + \beta_2^{(S)} \cdot v \left(\frac{1 + \alpha_{Cond}}{2 + \alpha_{Cond}} \right) + \epsilon_i + v \cdot \epsilon_{i,v} + \epsilon_{i,j}^b \tag{14}$$

where $b_{i,v}$ denotes the conditional bid of subject i conditional on the valuation v with $i \in \{1, \dots, 2616\}$ and $v \in \{0, \dots, 9\}$. $Cond \in$ {RedFriend, RedFoe, BlueFriend, BlueFoe} are denoting the treatment subjects are in. $\epsilon_{i,j}^b$ is the residual and again ϵ_i is the subject's specific random intercept effect and $\epsilon_{i,v}$ is the random slope effect of subject i. We keep $\beta_{1,2}^{(S)}$ constant over all treatments and search for the α which maximizes the log-likelihood of the model.[60] As we use a flexible model by allowing $\beta_1^{(S)}$ and $\beta_2^{(S)}$ to be different from zero (over all treatments) – i.e., assuming subjects to follow a bidding function similar to Equation 7 but with $\beta_1^{(S)} \neq 0$ and $\beta_2^{(S)} \neq 1$ – we need to fix one parameter (any one parameter from $\beta_1^{(S)}$, $\beta_2^{(S)}$, $\alpha_{BlueFriend}$, $\alpha_{BlueFoe}$,$\alpha_{RedFriend}$, α_{RedFoe}) to not under-specify the model. For simplicity and without loss of generality, we assume that the spite behavior towards friends is zero for Clinton voters.[61] To ensure robustness we alternatively fix spite behavior towards friends to zero for Trump voters ($\alpha_{RedFriend} = 0$). In a further alternative specification we assume that spite towards friends

[57] The data can be found here: https://www.census.gov/data/tables/2016/demo/income-poverty/glassman-acs.html (Glassman and United States Census Bureau, 2016).

[58] The data can be found here: http://doi.org/10.3886/ICPSR36399.v2 (Federal Bureau of Investigation, United States Department of Justice, 2016).

[59] Note, that we use a more flexible bidding model compared to the theoretically predicted equilibrium bidding function. Here we allow for a population specific bidding intercept, $\beta_1^{(S)}$, and we allow population specific conditional overbidding $\beta_2^{(S)}$. $\beta_1^{(S)}$ can be interpreted as joy of winning and $\beta_2^{(S)}$ could be interpreted as a general tendency to be spiteful or risk averse.

However, in Appendix C.6 we also structurally estimate α with the theoretically predicted equilibrium bidding function - the results are qualitatively very similar.

[60] We use a limited-memory modification of the Broyden-Fletcher-Goldfarb-Shanno quasi-Newton method to find the maximum while restricting all α to be in $(-1, 1)$.

[61] The reason for this assumption is that we need to fix one of the αs as all the other αs are calculated relative to this one - otherwise, our estimation would not converge due to too many degrees of freedom. Setting $\alpha_{BlueFriend} = 0$ is arbitrary - any other number would also work, and the estimates for the remaining αs would be adjusted. However, $\alpha_{BlueFriend} = 0$ seems like a reasonable benchmark as it is reasonable to assume that Clinton voters are not spiteful towards friends. Alternatively, we could also assume that $\alpha_{RedFriend} = 0$ - which does not change the results as can be seen in Tables 13 and 12.

	Bid									
	Clinton voters					Trump voters				
Constant	0.28*** (0.04)	0.21 (0.12)	−0.58 (0.39)	−0.49 (0.48)	0.36 (0.61)	0.48*** (0.06)	−0.13 (0.19)	0.24 (0.79)	−0.24 (0.90)	−1.61 (1.10)
Foe	0.04 (0.04)	−0.29** (0.10)	0.03 (0.04)	0.18 (0.49)	−0.18 (0.51)	0.05 (0.06)	1.00*** (0.14)	0.07 (0.06)	0.76 (0.77)	1.62* (0.80)
V	0.54*** (0.01)	0.62*** (0.02)	0.54*** (0.01)	0.54*** (0.01)	0.38*** (0.11)	0.55*** (0.01)	0.61*** (0.03)	0.55*** (0.01)	0.55*** (0.01)	0.76*** (0.18)
Foe:V	0.04*** (0.01)	0.04*** (0.01)	0.04*** (0.01)	0.04*** (0.01)	0.04*** (0.01)	−0.03* (0.01)	−0.02* (0.01)	−0.03* (0.01)	−0.03* (0.01)	−0.03* (0.01)
Age		0.003 (0.003)			0.003 (0.003)		0.01* (0.004)			0.01** (0.004)
Male		−0.01 (0.07)			−0.01 (0.07)		0.41*** (0.10)			0.47*** (0.10)
EduLow		0.001 (0.08)			−0.05 (0.08)		−0.08 (0.10)			−0.01 (0.10)
IncomeLow		−0.06 (0.06)			−0.05 (0.06)		0.003 (0.09)			0.01 (0.09)
Poverty(County)			−0.01** (0.004)	−0.01 (0.01)	0.01 (0.01)			−0.001 (0.01)	0.02 (0.01)	0.02 (0.01)
Poverty(State)			0.04* (0.02)	0.03 (0.02)	−0.01 (0.03)			0.02 (0.03)	0.02 (0.04)	0.001 (0.04)
Viol.Crimes(County)			−11.42 (27.96)	−196.54*** (38.06)	−158.29*** (47.08)			111.57* (50.56)	35.29 (57.99)	18.79 (71.92)
Crimes(County)			11.49 (9.75)	44.62*** (12.53)	41.02** (15.43)			−41.64** (14.01)	−5.68 (19.20)	8.66 (23.42)
MedIncome(State)			0.01 (0.004)	0.01* (0.01)	0.003 (0.01)			0.002 (0.01)	0.01 (0.01)	0.02 (0.01)
Unemp.rate(State)			0.02 (0.03)	−0.04 (0.04)	−0.07 (0.05)			−0.02 (0.05)	−0.02 (0.06)	−0.01 (0.08)
Foe:Age		0.0002 (0.002)			0.0000 (0.002)		−0.02*** (0.003)			−0.02*** (0.003)
Foe:Male		0.39*** (0.05)			0.42*** (0.05)		−0.41*** (0.08)			−0.51*** (0.09)
Foe:EduLow		0.09 (0.06)			0.16** (0.06)		0.13 (0.09)			0.11 (0.09)
Foe:IncomeLow		0.17*** (0.05)			0.16** (0.05)		−0.12 (0.07)			−0.14 (0.08)
V:Age		−0.001* (0.001)			−0.001* (0.001)		−0.001 (0.001)			−0.001* (0.001)
V:Male		−0.04** (0.01)			−0.04** (0.01)		−0.04** (0.02)			−0.05** (0.02)
V:EduLow		−0.03* (0.01)			−0.03* (0.01)		0.0001 (0.02)			0.002 (0.02)
V:IncomeLow		−0.01 (0.01)			−0.004 (0.01)		0.03* (0.02)			0.03* (0.02)
Foe:Poverty(County)				−0.01* (0.01)	−0.001 (0.01)				−0.03* (0.01)	−0.03* (0.01)
Foe:Poverty(State)				−0.001 (0.02)	−0.02 (0.02)				0.01 (0.04)	0.06 (0.04)
Foe:Viol.Crimes(County)				343.68*** (44.49)	347.63*** (44.94)				107.53* (49.14)	78.48 (52.35)
Foe:Crimes(County)				−63.52*** (13.42)	−74.59*** (13.63)				−57.54** (20.05)	−54.33* (21.83)
Foe:MedIncome(State)				−0.01** (0.01)	−0.01* (0.01)				−0.005 (0.01)	−0.01 (0.01)
Foe:Unemp.rate(State)				0.12** (0.04)	0.15*** (0.04)				0.01 (0.06)	−0.005 (0.06)
V:Poverty(State)					0.01* (0.005)					−0.001 (0.01)
V:Viol.Crimes(County)					−6.92 (7.96)					−6.30 (11.95)
V:Crimes(County)					2.80 (2.72)					2.13 (3.44)
V:Poverty(County)					−0.01*** (0.001)					−0.004* (0.002)
V:MedIncome(State)					0.002 (0.001)					−0.002 (0.002)
V:Unemp.rate(State)					0.01 (0.01)					0.003 (0.01)
Observations	15,220	15,220	15,220	15,220	15,220	9,400	9,400	9,400	9,400	9,400
Log Likelihood	−17,183.24	−17,172.01	−17,183.85	−17,137.77	−17,115.21	−11,263.12	−11,248.22	−11,263.26	−11,259.77	−11,252.47
Bayesian Inf. Crit.	34,443.51	34,536.63	34,502.52	34,468.14	34,596.37	22,599.42	22,679.41	22,654.60	22,702.50	22,852.58

Notes: *p<0.05;**p<0.01;***p<0.001;

Table 11: Mixed effects model of the conditional bidding with further controls.

V denotes the valuation. *Foe* denotes a dummy with value one if the opponent is a foe (i.e., opponent voted not the same candidate on election day) and zero otherwise. *EduLow* denotes bidders who have at most a high school degree. *IncomeLow* denotes bidders who have an income below 70*k* a year. *Age* denotes the subject's age. *Male* denotes a dummy with value one if the subject is male and zero otherwise. *Poverty(County)* denotes the poverty level reported in (United States Department of Agriculture, 2017) on the county level. *Poverty(State)* denote the poverty level reported in (Glassman and United States Census Bureau, 2016) on the state level. *Viol.Crimes(County)/Crimes(County)* denotes the percentage of (violent) crimes relative to the population of a county reported in (Federal Bureau of Investigation, United States Department of Justice, 2016). *Unemp.rate(State)* denotes the percentage of unemployed citizens in a state as reported in (Glassman and United States Census Bureau, 2016) and *MedIncome(State)* denotes the median income in a state as reported in (Glassman and United States Census Bureau, 2016). Standard errors are in parenthesis. Heterogeneity on the subject level is accounted for by subject-specific random intercept and subject-specific random slope effects. The number of observations differs slightly from Table 3, as we do not have location data of all the subjects and some subjects were not in continental United States during the experiment.

– for both Clinton and Trump voters – to be zero ($\alpha_{RedFriend} = \alpha_{BlueFriend} = 0$). Further alternative specifications are discussed in Appendix C.6.

If subjects would behave like risk neutral selfish agents in Nash-equilibrium we would expect $\beta_1^{(S)}$ to be zero (bid of zero for valuation of zero) and a $\beta_2^{(S)}$ of 1, as $\frac{1+\alpha_{Cond}}{2+\alpha_{Cond}}$ equals 1/2 for $\alpha = 0$. If subjects would not be driven by spite, α_{Cond} would be zero for all conditions, i.e., $\alpha_{Cond} = 0 \forall Cond \in$ {RedFriend, RedFoe, BlueFriend, BlueFoe}. The estimated $\beta^{(S)}$s are reported in Table 12, and the estimated α_{Cond} are reported in Table 13.

We can see from Table 12 that $\beta_1^{(S)}$ is significantly greater than zero and that $\beta_2^{(S)}$ is bigger than one. The latter might be explained by a general tendency to be spiteful, even towards friends, or alternatively by risk aversion. $\beta_1^{(S)}$ could potentially be a sign of joy of winning.

Concerning the estimation of α, we see in Table 13 that $\alpha_{BlueFriend}$ is not equal to zero if $\alpha_{RedFriend} = 0$ and vice versa. This means that Trump and Clinton voters do differ in their behavior towards friends. We also see that α_{RedFoe} is significantly different from zero (the estimate is negative, i.e. Trump voters behave less spiteful towards foes). More importantly, $\alpha_{BlueFoe}$ is significantly bigger than zero and is estimated at about .15. Hence, a Clinton voter would have a bidding slope of $\frac{1+.15}{2+.15} \approx .54$ if she is competing against a Trump voter, meaning that such a voter would bid roughly $\frac{\frac{1+.15}{2+.15}}{\frac{1}{2}} \approx 7\%$ more for any valuation compared to a Clinton voter who is competing against a fellow Clinton voter.

Table 12: Estimating the $\beta^{(S)}$s for Equation 14

	Bid		
	Fix $\alpha_{BlueFriend} = \alpha_{RedFriend} = 0$	Fix $\alpha_{RedFriend} = 0$	Fix $\alpha_{BlueFriend} = 0$
β_1	0.39*** (0.03)	0.42*** (0.03)	0.42*** (0.03)
$\beta_2 \cdot v\left(\frac{1+\alpha}{2+\alpha}\right)$	1.08*** (0.01)	1.11*** (0.01)	1.07*** (0.01)
Observations	26,160	17,440	17,440
Log Likelihood	−30,838.63	−20,436.44	−20,432.08
Akaike Inf. Crit.	61,689.26	40,884.88	40,876.17
Bayesian Inf. Crit.	61,738.29	40,931.48	40,922.77

Notes: *p<0.05;**p<0.01;***p<0.001;

The Table shows estimation results for the $\beta^{(S)}$s while fixing either $\alpha_{BlueFriend}$ to zero (Column 2), or fixing $\alpha_{RedFriend}$ to zero (Column 3) or fixing both (Column 1). Standard errors are in parenthesis.

Table 13: Estimation results of α for Equation 14

	Fix $\alpha_{BlueFriend} = \alpha_{RedFriend} = 0$	Fix $\alpha_{RedFriend} = 0$	Fix $\alpha_{BlueFriend} = 0$
α_{RedFoe}	-0.046* (0.021)	-0.071*** (0.021)	0.02 (0.033)
$\alpha_{BlueFoe}$	0.135*** (0.02)	0.044 (0.034)	0.154*** (0.022)
$\alpha_{BlueFriend}$	0 (Fixed)	-0.089** (0.028)	0 (Fixed)
$\alpha_{RedFriend}$	0 (Fixed)	0 (Fixed)	0.102** (0.038)

Notes: *p < 0.05;**p< 0.01;***p < 0.001;

The Table shows estimation results for the different α for Equation 14 while fixing either $\alpha_{BlueFriend}$ to zero (Column 2), or fixing $\alpha_{RedFriend}$ to zero (Column 3) or fixing both (Column 1). Standard errors are in parenthesis.

Result 6.1. *Trump voters have an α towards foes which is significantly smaller than zero.*

Result 6.2. *Clinton voters have an α of .15 towards foes (compared to friends) which is significantly greater than zero.*

Result 6.3. *For any given valuation Clinton voters bid 7 % more if competing with foes compared to their bidding towards friends.*

C.6. Structural estimation with theoretical bidding function

In section C.5, we allowed for a flexible model to structurally estimate the spite factors. For that purpose we allowed for an intercept $\beta_1^{(S)}$ and a slope $\beta_2^{(S)}$. However, this flexibility led to the need to fix one of the α's. In this section we use a more restricted model and assume that subjects follow directly the theoretical bidding function depicted by Equation 7, i.e., we assume $\beta_1^{(S)} = 0$ and $\beta_2^{(S)} = 1$. The corresponding α's are shown in Table 14 in the first column. We also estimate the α's for a somewhat intermediate model by assuming only $\beta_2^{(S)}$ be zero and allowing for a flexible intercept $\beta_1^{(S)}$. The corresponding α's are shown in the second column of Table 14. Obviously the resulting α's increase strongly. However, the differences between the α's in the treatments prevail qualitatively the same as reported in Table 13. More specifically, it is evident that $\alpha_{RedFriend}$ is again significantly higher than $\alpha_{RedEnemy}$, indicating that Trump voters can be interpreted as less spiteful towards foes. It is also evident that $\alpha_{BlueFriend}$ is again significantly smaller than $\alpha_{BlueEnemy}$, indicating that Clinton voters can be interpreted as substantially more spiteful towards foes. Thus, all results from Section 4 are robust to these alternative specifications.

Table 14: Structural estimation results of α for Equation 14 while assuming a bidding function similar to Equation 7.

	Fix $\beta_1^{(S)} = 0$, $\beta_2^{(S)} = 1$	Fix $\beta_1^{(S)} = 0$
$\alpha_{RedFriend}$	0.511*** (0.047)	0.254*** (0.04)
α_{RedFoe}	0.388*** (0.04)	0.155*** (0.035)
$\alpha_{BlueFoe}$	0.589*** (0.038)	0.317*** (0.034)
$\alpha_{BlueFriend}$	0.357*** (0.032)	0.13*** (0.029)
Notes:	*p < 0.05;**p< 0.01;***p < 0.001;	

The Table shows estimation results for the different α for Equation 7, i.e., where the intercept is set to zero and the slope is set to one (i.e., $\beta_1^{(S)} = 0 \wedge \beta_2^{(S)} = 1$) in the first column. The second column shows the estimation results for the different αs while allowing the intercept to be non-zero. Standard errors are in parenthesis.

D. Instructions and control questions

D.1. Instructions

The following depict the instructions used in the experiment:

Welcome to this experiment in the economics of market decision making. If you follow these instructions carefully and make good decisions you will earn a considerable amount of money that will be paid to you within one week to your MTurk account. We ask that you pay close attention to the instructions.

Note that one of the main guidelines in experimental economics is that we do NOT deceive participants (see https://en.wikipedia.org/wiki/Experimental_economics). Hence, all rules and restrictions will indeed be implemented in the way we describe them. We go to great lengths to ensure that assignments, randomization of variables and rules are implemented exactly in the way they are presented here to you!

In this experiment, you will be assigned an opponent. Your payoff will depend on his/her decisions and his/her payoff may depend on your decisions. Typically every person is assigned, one opponent.

To comply with the non-deception-rules of economics we also need to inform you about a technical issue: It may happen that more than one person is assigned to another person. In such a (rather rare) case it will be randomly decided choose decision will be payoff relevant to this other person. Thus, your payoff will always depend on the decision of somebody else. Your decision will influence the payoff of your assigned partner in most cases. It, however, may happen that your decision does not impact the payoff of your partner as somebody else's choice has been determined payoff-relevant for your partner.

In this part of the experiment, you will participate in an auction.

Please read the instructions very carefully! At the end of the instructions, we will have control questions. For each correctly answered control question you will be paid 10 cents. Failing two or more control question will lead to your exclusion from the experiment. You will be competing with one other bidder to purchase one unit of a fictional commodity, which we will call X.

At the end of the experiment, you will resell X to the experimenters, if you win the auction.

Resale Value
The resale value will be determined by a computerized ten-sided die roll.
The resale value of X will be either \$0, \$1, \$2, \$3, \$4, \$5, \$6, \$7, \$8 or \$9.

Each value is on one side of the die and each value is equally likely to be rolled. Therefore, there is a 10% chance that X will be worth \$0, a 10% chance X will be worth \$1, and so on. The same rule applies to your competitor, i.e., he is competing against you for the same unit of commodity X. However, the resale value for you and your competitor are drawn independently of one another. For him, another ten-sided die will be rolled, which has the same values as your die and the same chances as your die. To obtain the commodity X, you will bid in one auction against your competitor.

Contingent bid decision

Both you and your competitor will have to make bidding decisions depending on each possible die roll. Thus, you will say how much you bid for X if the die roll would be \$0, how much you bid if the die roll is \$1 and so on. We call this decision the contingent bid.

Real Bid

After your contingent bid decision both dice (your die and your opponents die) will be thrown. The outcome of the die will determine your real bid. Imagine you have made the following example contingent bid decisions:

[[Figure 1a can be seen]]

If for example, your die roll is \$4, your real bid will be (according to your contingent bids) \$2.10.

If for example, your die roll is \$2, your real bid will be (according to your contingent bids) \$1.07.

Outcome of the auction

- The individual with the highest real bid will win the commodity X and resale it to the experimenters at the end of the experiment at the value of their die roll.
- The individual with the lower real bid will not obtain the commodity X.
- The winning individual (the individual bidding the highest real bid and obtaining the commodity) will pay his bid.
- The losing individual will neither pay a bid nor will he obtain X.

Calculation of your income

Your payment for this task will depend on your resale value (the die roll), your real bid, and your opponent's real bid.

- The winning individual will obtain the following payment:
  Payment = Resale Value of X (=your die roll) - Your own real bid
- The losing individual will obtain the following payment:
  Payment = 0.

You make money by winning the auction at a favorable price.

- If you win an auction at a price that is below your resale value, then your profit is:

  - Your resale value - your real bid.
  - For example, if your resale value is \$7 (if your die rolled 7) and you win the auction at a real bid of \$4, then your profit in this auction is: \$7 - \$4 = \$3.

- Note, if you win the auction at an unfavorable price (at a price that is above your resale value), you will lose money (the lost money will be subtracted from further payments in the experiment).
- If you do not win the auction (if your real bid is below the real bid of your opponent), your profit for this task is \$0.
- In the case of a tie (you and your opponent bid the same for X), one of you will randomly be chosen as the winner and the other will consequently lose the auction.

Example 1: Suppose for example that your die roll shows 7 (=resale value is \$7) and your contingent bid for 7 is 5. Thus, your real bid is \$5. Suppose your bid is the highest so that you receive X.
Your earnings would be: \$7-\$5=\$2.

Example 2: Suppose for example that your die roll shows 7 (=resale value is \$7) and your contingent bid for 7 is 2.45. Thus, your real bid is \$2.45. Suppose your bid is the highest so that you receive X.
Your earnings would be: \$7-\$2.45=\$4.55.

Example 3: Suppose for example that your die roll shows 7 (=resale value is \$7) and your contingent bid for 7 is 2.45. Thus, your real bid is \$2.45. Suppose your bid is not the highest so that you do not receive X.
Your earnings would be: \$0.

Example 4: Suppose for example that your die roll shows 3 (=resale value is \$3) and your contingent bid for 3 is 2.45. Thus, your real bid is \$2.45. Suppose your bid is the highest so that you receive X.
Your earnings would be: \$3-\$2.45=\$0.55.

Example 5: Suppose for example that your die roll shows 3 (=resale value is \$3) and your contingent bid for 3 is 0.45. Thus, your real bid is \$0.45. Suppose your bid is the highest so that you receive X.
Your earnings would be: \$3-\$0.45=\$2.55.

Example 6: Suppose for example that your die roll shows 3 (=resale value is \$3) and your contingent bid for 3 is 3.45. Thus, your real bid is \$3.45. Suppose your bid is the highest so that you receive X.
Your earnings would be: \$3-\$3.45=-\$0.45.
The negative amount will be subtracted from further earnings in this experiment.

[[Now subjects had to answer the control questions shown in Appendix D.2]]

Individuals who have indicated to vote for Donald Trump at the beginning of the experiment were assigned to a group called "red".
Individuals who have indicated to vote for Hillary Clinton at the beginning of the experiment were assigned to a group called "blue".

[[Opponent is a Trump Voter:]]
Your assigned opponent indicated to vote for Donald Trump. Hence, your opponent was assigned to be a member of the group "red".

[[Opponent is a Clinton Voter:]]
Your assigned opponent indicated to vote for Hillary Clinton. Hence, your opponent was assigned to be a member of the group "blue".

D.2. Control Questions

The following control questions have been asked after the instructions of the auction.

Please answer the following control questions.
Note: This decision is payoff-relevant and will influence your payment!

Assume that your resale value of X is $5 and your contingent bid for 5 is $2 and you win (your real bid is higher than the real bid of your opponent):

- You gain $3
- You gain $2
- You gain $5
- You gain $1
- You gain $0

Assume that your resale value of X is $5 and your contingent bid for 5 is $2 and you don't win (your real bid is lower than the real bid of your opponent):

- You gain $3
- You gain $2
- You gain $5
- You gain $1
- You gain $0

Assume that your resale value of X is $5 and your contingent bid for 5 is $6 and you win (your real bid is higher than the real bid of your opponent):

- You gain $3
- You gain $2
- You gain $5

- You gain $1
- You gain $0

Imagine you and your opponent made the following contingent bid decision:
[[Figure 1a can be seen]]

Suppose your die rolls an 8 (your resell value is $8) and your opponents die rolls a 6 (your opponents resell value is $6). What would your profit in this example be?

- You gain $2
- You gain $5.09
- You gain $1.17
- You gain $3.92
- You gain $0

D.3. Belief elicitation

After indicating the conditional bid for all possible die rolls subjects in the third and fourth wave were also asked to indicate their bidding belief. To do so subjects were instructed as follows:

Now you will be asked to guess the bids of your opponent!

Thus, you are asked to indicate which contingent bid, for each of the possible resale values (die rolls), you think your opponent will choose.

After the experiment, the resale value for your opponent will be determined by a ten-sided die. If your guess of the contingent bid for this randomly drawn resale value is correct (i.e. if your indicated guess is within a range of 10 cents of the actual bid of your opponent) you will get an additional 20 cents.

Thus, the better you guess the higher is your chance of getting an additional payment of 20 cents.

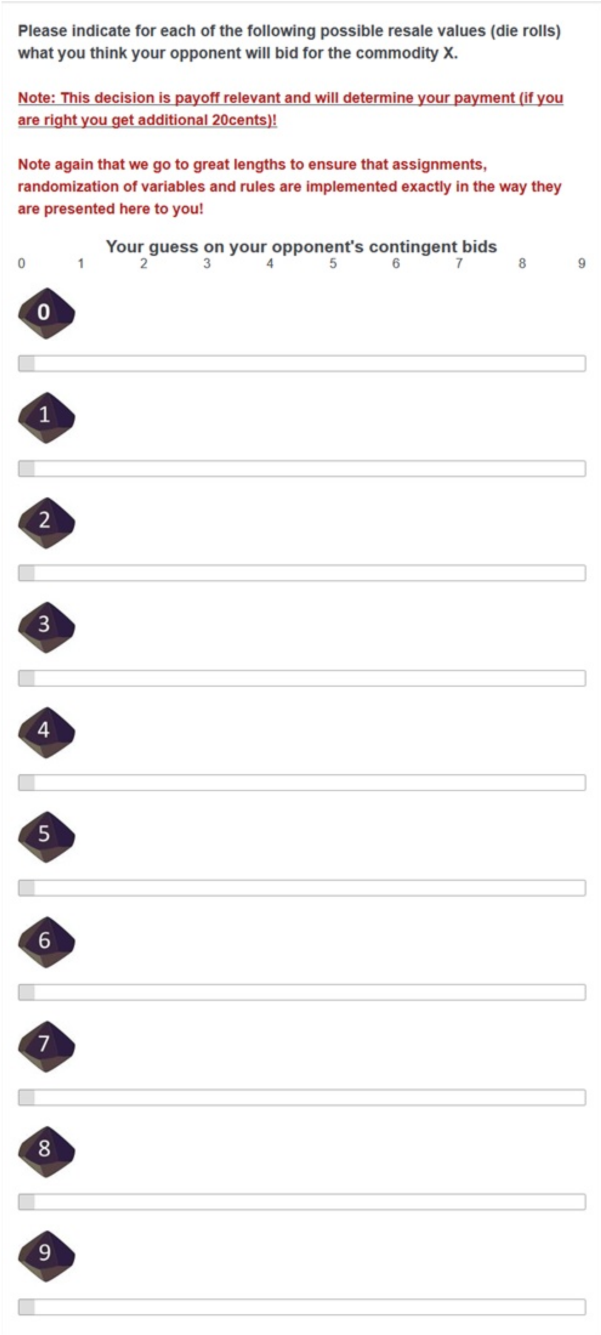

Figure 7: Screenshot of the belief elicitation.