Name Similarity Encourages Generosity: A Field Experiment in Email Personalization

In a randomized field experiment with the charitable giving platform DonorsChoose.org ($N = 30{,}297$), we examined whether potential donors were more generous toward beneficiaries who shared their surnames. DonorsChoose.org allows classroom teachers to solicit online donations to support proposed classroom projects. The platform advertises these projects by sending emails to potential donors. Name-matched potential donors were more likely to open an email, click on a link in the email, and make a donation, and they donated more than twice as much compared to those who were asked to donate to a teacher who did not share their own surname. Our results suggest that uniting people with shared names is an effective individual-level approach to email personalization, even when name-matching is transparently designed to promote generosity. We also tested for name-letter effects, finding that potential donors who shared a first letter but not an entire name with teachers also behaved more generously. This result supports the principle of "implicit egotism," which suggests that people are drawn to stimuli that remind them of themselves.

Keywords: field experiment, charitable giving, individual targeting, personalization

Prior to the 2016 US presidential election, Hillary Clinton's campaign sent emails to potential donors with the subject, "[Names] for Hillary" where the given name of the potential donor was individually customized. This email campaign highlighted how technology enables marketers to target consumers with increasing granularity. Indeed, already 67% of US marketers report personalizing email messages to target individual consumers (eMarketer 2016). However, open questions remain about how to effectively use this increasingly available technology. As suggested by this example, one individual-level targeting strategy is to personalize by using a recipient's name. This may be effective for several reasons. To begin, people pay special attention to their own name (Cherry 1953), and they tend to like others who are similar to themselves (Byrne 1971), even when the similarity is coincidental (Faraji-Rad et al. 2015, Jiang et al. 2010, Woolley and Fishbach 2017). In addition, there has been wide documentation of preferential treatment toward one's own group members (e.g. Tajfel and Turner 1979), and recent work has suggested that neural responses to social groups are similar regardless of the criteria on which they are based (Cikara et al. 2017). Thus, the Clinton campaign created a social group around a coincidental form of similarity: a shared name. In this paper, we explored the related effect of matching a potential donor to a person in need based on name. That is, are email recipients more likely to donate money to help someone who shares their surname?

Linking people by name may shrink the social distance that naturally exists between strangers, which has the capacity to boost charitable giving (Loewenstein and Small 2007). People who are close to us (either as family members or friends) tend to also be similar to us, and since we tend to donate more to personally relevant charities such as those that target the illnesses of our friends and loved ones, we tend to donate more to those who are similar to us (Small and Simonsohn 2008). When applied beyond close relationships, similarity may itself lead to feelings of social closeness, and hence generosity. For instance in one correlational study, lenders on the micro-lending platform Kiva tended to favor self-matching genders, professions, and first-name letters (Galak et al. 2011). Accordingly, emphasizing the similarities between a potential donor and recipient should induce a sense of closeness, which should in turn prompt generosity.

Though research suggests that similarity engenders generosity, most of these studies have manipulated similarity subtly. In contrast, we know relatively little about how potential donors might respond to *overt* attempts to highlight their similarities to potential recipients. The effect of a message can be very different if consumers believe they are the subject of a persuasion attempt (Campbell and Kirmani 2000, Friestad and Wright 1994). Most past research which has explored the positive effect of a matched name on altruistic behavior has presented it as a coincidence rather than an overt persuasion attempt (Burger et al. 2004, Guéguen et al. 2005, Oates and Wilson 2002); for example, when the requester herself happens to have the same name as the potential donor (Burger et al. 2004). Can an effect of name matching also occur in the absence of serendipity, when the charitable organization is clearly using the name of the donor as part of the appeal? Burger and colleagues also found that experimental participants donated more to a charity when the requester shared their first name, but not when a photographed person who would actually receive the help did (Burger et al. 2004). The authors argued that the coincidental similarity between the requester and the participant created a sense of closeness, known as a "unit relationship," which may be absent when the request is made by a third party. For instance, there are relational benefits when a person coincidentally meets a fellow Californian in Charlotte, but simply telling someone that a fellow Californian lives in Charlotte doesn't seem to engender the same response. Researchers in marketing have also found that consumers may feel as though their privacy has been violated if they believe their personal characteristics are being used as tools of persuasion (Awad and Krishnan 2006, Song et al. 2016, Zhu et al. 2017). For instance, a name-personalized email greeting can have a negative effect on response for this reason, particularly when the sender is relatively unfamiliar (Wattal et al. 2012). Taken together, these findings suggest that there may be a potential for a backfire effect to personalizing an email with a name.

In this paper, we explored whether potential donors were more generous when they were overtly paired with recipients who shared their surnames. We partnered with DonorsChoose.org, one of the largest educational charities in the US to conduct a large field experiment. DonorsChoose maintains an online platform where public school K-12 teachers can seek funding for classroom projects that are otherwise not funded by their schools or school districts. Individual donors browse the DonorsChoose web site or respond to periodic email solicitations and donate any amount to projects that seem worthwhile. Donors who support funded projects receive photos and other feedback from the recipient teacher and his or her classroom as the project runs and after it ends. We randomly assigned potential donors to receive an email about a project led by either a teacher with a matching surname or a random non-matching surname. This procedure did not involve deception; the database of potential donors included about 1.5 million donors who had donated within the past three years, sufficiently large to facilitate actual matching.

This study advanced the literature in three ways. First, it constituted a highly powered, ecologically valid investigation of the hypothesis that people are more generous towards similar others, even when that point of similarity is superficial (Small et al. 2007). Second, and more specifically, it uncovered how consumers respond to overtly personalized emails. Finally, it tested whether people are indeed attracted to incidental features of the environment that mirror their own identities—an ecologically valid test of the "implicit egotism" principle (Pelham et al. 2002, Pelham and Carvallo 2015). Relevant research provided evidence that people favor self-referential identifiers such as the letters of their name (Nuttin 1985) or the numbers of their birthday (Alter 2009, Kitayama and Rarasawa 1997) because they unconsciously prefer self-relevant stimuli. Though much of the research in this area is controversial, its adherents have claimed that implicit egotism affects highly consequential decisions, such as who people marry (Jones et al. 2004, Pelham and Carvallo 2015), where they live (Pelham et al. 2002), what they buy (Brendl et al. 2005), to whom they make charitable donations (Chandler et al. 2008), and how they behave in the workplace (Anseel and Duyck 2008, Nelson and Simmons 2007, Pelham et al. 2002, Pelham and Carvallo 2015, Polman et al. 2013).

These results are controversial because almost all of the evidence for real-world effects rests on secondary data. Accordingly, researchers have argued that evidence for implicit egotism effects may actually reflect methodological shortcomings. For example, reverse causality may be a concern in one study (Anseel and Duyck 2008) because people often name businesses after themselves rather than choose to work at companies with similar names (Simonsohn 2011b). Similarly, rather than marrying a person because their surname shares a first letter (Jones et al. 2004), people often marry their former spouses, and thus their name-letters match on account of marriage and not the reverse (Simonsohn 2011a). In addition, many secondary data studies may inadequately account for third-variable explanations. For example, many names correlate highly with ethnicity, and people may alternatively be favoring their ethnic in-group (Simonsohn 2011a). Note that this concern also potentially applies to experimental evidence (e.g. Burger et al. 2004). In our experiment, we controlled for this potential confound of name match and ethnicity match. Furthermore, some analyses of prior evidence of implicit egotism may involve cherry-picking letters or data sets to test (McCullough and McWilliams 2010, 2011, Simonsohn 2011a, b). For example, results may be misleading if only testing if k-letter names strike out more often than average in baseball (Nelson and Simmons 2007) rather than checking across all letters, an analysis which revealed that p-letter names also struck out more often than average (McCullough and McWilliams 2010). Lastly, there have been other specific analytical concerns. For example, there has been concern over performing analysis without accounting for nested data structures (Dyjas et al. 2012; Gallucci 2003). Therefore, a randomized field experiment on name-letter effects could go far to allay some of the concerns in this area. Specifically, we tested for name letter effects without the possibility of reverse causality, we reduced the likelihood of third-variable explanations through random assignment in a yoked-design and by controlling for ethnicity, and we tested across all letters without cherry-picking an existing data set.

Method

We report how we determined our sample size, all data exclusions, all manipulations, and all measures in the study (Simmons et al. 2012). We pre-registered our plan for conducting this research prior to collecting any data, and made it publicly available.[1]

Participants. DonorsChoose provided us with a list of 52,601 email addresses, all corresponding to a prior donor whose surname matched at least one teacher with an active project on the site at the time of the experiment. To minimize the possibility that name-matching teachers and donors might be related, DonorsChoose filtered the list to exclude all donors who had been introduced to the site by a teacher.

[1] https://aspredicted.org/5xp2f.pdf

We randomly reduced the size of the list so that every teacher was matched with two potential donors—one with a matching name, and one with a non-matching name. This allowed us to yoke each name-matched donor to a name-mismatching donor who received the same email solicitation, and to use the same teacher-projects as stimuli in both conditions (each project was seen by one participant in each condition). We also prevented more than two potential donors from responding to each teacher-project to prevent the background variables (gender, location, ethnicity, nature of the project, poverty of the school, etc.) of any one teacher-project from having an outsized influence on our results. To ensure that each teacher-project appeared as a stimulus in both conditions exactly once, we reduced the number of teachers in some cases, and reduced the number of donors in others. For example, if there were 25 teachers with a surname and 100 donors with the same surname, we randomly reduced the number of *donors* to 50 and kept all 25 teachers. Conversely, if there were 25 teachers with a surname and 40 donors with that surname, we randomly reduced the number of *teachers* to 20 and kept all 40 donors.

This procedure left us with a sample of 15,370 projects and 30,740 potential donors across the two conditions. Since some emails failed to reach their intended recipients, the final sample was 15,142 emails in the name-mismatch condition and 15,155 in the name-match condition (N = 30,297).

Procedure. We randomly assigned participants to one of two conditions: a name-match condition where the donor and teacher shared a surname, or a name-mismatch condition where the donor and teacher did not share a surname.

Each email recipient received an email with the subject line, “Treat (prefix: Mrs./Ms./Mr.) (teacher surname)’s classroom this summer!” The words in parentheses were replaced by the appropriate words corresponding to an actual teacher. Both conditions saw the same email subject and body text. The only difference was whether or not the surname of the teacher was the same as the surname of the potential donor. The text of the email can be seen in Figure 1.

Our dependent measures were: whether recipients opened the email (yes/no); whether recipients clicked on the link in the email (yes/no); whether recipients donated to support the project (yes/no); and how much the recipient donated.

Results

First we report the results without attempting to control for other variables. A summary of these results appears in Table 1. Name-matched email recipients were significantly more likely to open the email with the name-matched subject line, doing so 35.1% of the time compared to 27.6% of the time in the name-mismatch condition, $\chi^2(1, N = 30{,}297) = 197.3$, $p < .001$, $d = .162$. Similarly, name-matched email recipients were significantly more likely to click on the link in the email, doing so 6.9% of the time compared to 4.6% of the time in the name-mismatch condition, $\chi^2(1, N = 30{,}297) = 70.2$, $p < .001$, $d = .096$. Conditional on opening the initial email, the likelihood of clicking on the link was significantly greater in the name-match condition (19.6%) compared to the name-mismatch condition (16.8%), $\chi^2(1, N = 9{,}492) = 12.3$, $p < .001$, $d = .072$. Those in the name-match condition were significantly more likely to donate than those in the name-mismatch condition $\chi^2(1, N = 30{,}297) = 8.4$, $p = .004$, $d = .033$. Of the 43 donations, 31 (72.1%) were made by those in the name-match condition. On average, those in the name-match condition (M = \$0.20, SD = \$7.98) donated more than twice as much as those in the name-mismatch condition (M = \$0.09, SD = \$5.46). The data were heavily skewed, since, as tends to occur with email solicitations, most people did not donate. Thus, we conducted a significance test using a nonparametric Mann-Whitney U, which revealed the amount donated to be higher in the name-match group $Z = 2.90$, $p = .004$. A significant result was also obtained by calculating an ANOVA on a variable computed by adding a trivial amount and natural log-transforming the donation amount $F(1, 30295) = 8.02$, $p = .005$, $d = .016$. To summarize, these results indicate that matching a donor to a teacher with the same surname improved all of the outcomes we measured.[2]

Controlling for Ethnicity Matching. As has been suggested elsewhere (Simonsohn 2011a), observed effects attributed to name-matching could alternatively be due to in-group favoritism. That is, certain names convey information about ethnicity, and people may favor their own ethnic groups rather than favoring their own surnames. While our data do not contain information about ethnicity, to attempt to control for this possibility we turned to data from the 2000 US census. The data set provided the percentage likelihood that each surname belongs to a particular ethnicity, including percentages for six ethnicities: white, black, Asian / Pacific Islander, American Indian/Alaskan Native, two or more races, and Hispanic.[3] We appended these percentages to our data for both the potential donor's surname and the corresponding teacher's surname.

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[2] We also ran an analysis that excluded the yoked-pairs of email send failures. That is, if an email about a teacher-project didn't reach a potential donor in one group, we also excluded the corresponding teacher-project and potential donor from the other group. This analysis is nearly identical, with both cell sizes of 14,949 for a total N of 29,898. Potential donors in the name-match condition were more likely to open the email (5247, 35.1%) than those in the name-mismatch condition (4107, 27.5%), $\chi^2(1, N = 29{,}898) = 202.2$, $p < .001$. Those in the name-match condition were also more likely to click on the link (1030, 6.9%) than those in the name-mismatch condition (687, 4.6%), $\chi^2(1, N = 29{,}898) = 49.2$, $p < .001$. Name-matched potential donors were more likely to donate (31, 0.2%) than name-mismatched potential donors (11, 0.1%), $\chi^2(1, N = 29{,}898) = 9.5$, $p = .002$, and on average, they donated more (M = \$0.20, SD = \$8.03 vs. M = \$0.09, SD = \$5.49). A Mann-Whitney U test revealed the amount donated to be higher in the name-match group $Z = 3.09$, $p = .002$. A similar result obtained by computing an ANOVA with a natural-log transformed payment amount $F(1, 29896) = 8.9$, $p = .003$.

[3] These are the labels used in the census data.

For descriptive purposes we first report the most likely ethnicity of each name. That is, for each name, we identified the ethnicity with the highest likelihood. The experimental data contained 26,627 (87.9%) names which are most likely to be white, 2,752 (9.1%) names which are most likely to be Hispanic, 449 (1.5%) names which are most likely to be black, 416 (1.4%) names which are most likely to be Asian / Pacific Islander, and 6 names (< .1 %) which are most likely to be American Indian / Alaskan native. Two or more races was not the most likely ethnicity of any name in the data set.

Because we inferred ethnicity from the surname, the most likely ethnicity of the teacher and the potential donor matched 100% of the time in the name match condition. However, some names were not in the census, and thus not included in our analysis (15,130 included in analysis from the name-match condition). In the name-mismatch condition, 11,784 (77.8%) matched on most likely ethnicity. This high rate of ethnic matching (N = 26,914) was coincidental rather than planned.

To attempt to control for surname ethnicity matching, we next present results when only examining the cases for which the most likely ethnicity of the potential donor matched the most likely ethnicity of the teacher. As seen in Table 1 in the “Ethnicity Match” column, all our reported outcomes were robust to this selection criterion. Specifically, those in the name-match condition were more likely to open the email (5307, 35.1%) than in the name-mismatch condition (3271, 27.8%), $\chi^2(1, N = 26{,}914) = 163.4$, $p < .001$, $d = .156$. Those in the name-match condition were more likely to click on the link in the email (1038, 6.9%) than in the name-mismatch condition (574, 4.9%), $\chi^2(1, N = 26{,}914) = 46.6$, $p < .001$, $d = .083$. Conditional on opening the email, those in the name-match condition were more likely to click on the link in the email (1038, 19.6%) than in the name-mismatch condition (574, 17.5%), $\chi^2(1, N = 8{,}578) = 5.4$,

p = .021, d = .05. Those in the name-match condition were more likely to donate (31, 0.2%) than those in the name-mismatch condition (10, 0.1%), $\chi^2(1, N = 26{,}914) = 6.3$, p = .012, d = .031, and on average, they donated more (M = \$0.20, SD = \$7.98 vs. M = \$0.11, SD = \$6.17). A Mann-Whitney U test revealed the amount donated to be higher in the name-match group Z = 2.51, p = .012. A similar result obtained by computing an ANOVA with a natural-log transformed payment amount $F(1, 26912) = 5.8$, p = .016. As shown in the "Yoked Ethnicity Match column of Table 1, the results and conclusions were unchanged if we alternatively excluded both the ethnicity mismatch from the name-mismatch condition and the yoked pair in the name-match condition.[4]

Because some names are more diagnostic of ethnicity than others (that is, certain names are more uniquely associated with exactly one race), we also tested for an effect of the diagnosticity of a name among the ethnic match subset. Results of this analysis do not change our conclusions and are available in a web appendix.

One could argue that the above methods, by using only information about the *most* likely ethnicity for each name, fails to utilize all of the ethnicity information available in the census data. We therefore decided to additionally calculate Euclidean distances for each name pair. Euclidean distance is a measure of the distance between the two names in multidimensional space (using all of the ethnicity percentages), where smaller numbers indicate a higher likelihood

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[4] Specifically, potential donors in the name-match condition were more likely to open the email (4102, 35.3%) than those in the name-mismatch condition (3214, 27.6%), $\chi^2(1, N = 23{,}258)$ = 156.0, p < .001, d = .165. Those in the name-match condition were also more likely to click on the link (814, 7.0%) than those in the name-mismatch condition (562, 4.8%), $\chi^2(1, N = 23{,}258)$ = 49.2, p < .001, d = .092. Name-matched potential donors were more likely to donate (25, 0.2%) than name-mismatched potential donors (10, 0.1%), $\chi^2(1, N = 23{,}258) = 6.4$, p = .011, d = .033, and on average, they donated more (M = \$0.19, SD = \$7.78 vs. M = \$0.11, SD = \$6.21). A Mann-Whitney U test revealed the amount donated to be higher in the name-match group Z = 2.54, p = .011. A similar result obtained by computing an ANOVA with a natural-log transformed payment amount $F(1, 23256) = 5.8$, p = .016.

of a name-pair being of the same ethnicity probability distribution. Our results were also robust to this method of controlling for ethnicity matching. The results using a 25th percentile Euclidean distance selection criterion are presented in Table 1. The full analysis is reported in the web appendix.

Name-Letter Effects. One secondary goal of this paper was to test for implicit egotism. The results we have presented thus far do not reflect implicit processes, as potential donors can clearly see that the advertised teacher shares a surname and may explicitly choose to donate for that reason. However, many studies on implicit egotism have instead looked for surname first-letter effects (Nuttin 1985). Though we did not design the experiment to test this hypothesis, it may be that people are willing to donate more to a project led by a teacher whose last name shares the same initial letter as their own surname. We tested for this possibility by examining our name-mismatch condition. By chance, 932 of the name-mismatched pairs shared the same first letter. As before, to control for ethnicity we ran our analysis on only the subset who matched on most likely ethnicity. This left 751 name-letter matches, which included no full name matches. This analysis is important because others have argued that observed name-letter effects may be driven by full name matches, which can occur for nonrandom reasons (in the case of marriages, marrying a former spouse; in the case of employment, working for a family business) and thus may reverse the causal direction (Simonsohn 2011a, b). Table 2 summarizes the results. We found that all dependent measures were directionally supportive, though the effect sizes were predictably modest since name-letter effects are smaller than other dimensions of social distance (Galak et al., 2011). We found a significant difference in the incidence of opening the email (31.3% vs. 27.5%), $\chi^2(1, N = 11{,}784) = 5.0$, $p = .025$, $d = .041$. Additionally, while not significant at conventional levels, the incidence of donating was higher among those who matched on surname first letter (0.3%) than in those who did not (0.1%), $\chi^2(1, N = 11{,}784) = 3.1$, $p = .078$, and on average they donated more (M=$0.41, SD=$10.34 vs. M=$0.09, SD=$5.77), Z = 1.77, $p = .078$ as evaluated with a Mann-Whitney U-test. An ANOVA on the natural-log transformed amount revealed this difference to be significant $F(1,11782) = 3.93$, $p = .047$, $d = .052$, however, the assumption of homogeneity of variance was violated, suggesting the nonparametric Mann-Whitney test may be more appropriate. Participants also clicked on the link more often (5.7% vs. 4.8%), though this difference failed to reach statistical significance $\chi^2(1, N = 11{,}784) = 1.3$, $p = .261$, $d = .021$. In sum, these results are largely consistent with the predictions of "implicit egotism." [5]

Name Commonness. We examined the effect of name commonness because past research has suggested that this variable may be an important moderator of the coincidence-driven "unit relationship" described by Burger et al. (2004). Specifically, stronger unit relationships are thought to occur when circumstances are less likely; a Californian feels a relationship when she encounters a fellow Californian in Charlotte, but not when she encounters one in Los Angeles. A similar effect also applies to implicit egotism (Pelham et al. 2005). Specifically, people are assumed to show greater bias when the identifier is more uniquely associated with the self, as would be the case with an uncommon name. Therefore, we should observe that the commonness (uniqueness) of a name should matter in the name-match condition only. That is, an interaction with condition.

With the exception of the "clicked" dependent measure, we did not find evidence for this hypothesis. The results are presented in the web appendix. These results make sense given our

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[5] For all variables, the results are unchanged when instead computed by ANOVA with random effects.

design: there was no pretense of the full name-match being coincidental, and thus it is likely some process other than the “unit relationship” (Burger et al. 2004) drove our results.

However, because surname first-letter effects are thought to be a result of “implicit egotism,” we also tested for interactive effects of name commonness with surname first-letters. Consistent with an implicit egotism explanation, we did observe this interaction on the likelihood of donation and the amount donated. The full analysis is reported in the web appendix.

Discussion

In a large field experiment, we found that people were more likely to engage with an email request for donation, were more likely to donate, and donated more on average when the donations aided a classroom led by a teacher who shared their own surname than when the teacher did not share their surname. These results were robust across analyses controlling for ethnicity matching, suggesting that there may be an effect above and beyond ethnic in-group favoritism. We also demonstrated a very small name-letter effect in our name-mismatch condition when controlling for ethnicity matching. Participants were more likely to open the email when the teacher shared the same surname first letter. Because we obtained these data in a randomized field experiment on pairs matched for ethnicity without the possibility of the effect being driven by full-name matches, we believe this is the most unbiased test of implicit egotism in the real world to date. The effect sizes observed for these name-letter effects are very small, which may explain why they fail to be detectable in some archival studies.

Note that this was actually the second experiment conducted by DonorsChoose on name matching. However, their first experiment had a minor selection issue involving assignment to condition. While consistent with the reported findings, we therefore do not report the results of that experiment here. None of the participants from the first experiment participated in our reported experiment.

This campaign was very successful for DonorsChoose. The average open rate across all of their email campaigns is about 20%, and they observe click rates between two and three percent (J. Penny, personal communication, July 26, 2017), suggesting that both our treatment (35.1% opened; 6.9% clicked) and control groups (27.6% opened; 4.6% clicked) performed well. Accordingly, DonorsChoose has been motivated to subsequently apply the lessons learned from this experiment to replicate its success in eliciting donations on numerous occasions. While they no longer use a control group, they have observed similar levels of engagement and donation on subsequent iterations of what has become an annual campaign. They have successfully used name matching to raise hundreds of thousands of dollars, and have drawn accolades from their donors, some who have described the email as "a brilliant ad campaign." Our findings and anecdotes such as this one highlight an important feature of the campaign: potential donors were aware of manipulation.

The explicit nature of the full name match is managerially important because marketing scholars have long debated whether identity matching backfires when the match is contrived (e.g. Arora et al. 2008, Song et al. 2016). While there are many benefits to personalization of marketing appeals, researchers have suggested that personalization may imply a violation of privacy (e.g. Awad and Krishnan 2006). Here, we demonstrated that in aggregate a personalized campaign was more effective than a similar one that was not personalized, even if some potential donors were deterred by the personalized marketing appeal. Furthermore, using their identity to persuade them did not appear to disenchant them. In addition to the data provided by DonorsChoose, a recent industry study suggested that the average open rate for email marketing was 27% and the average click rate was 3.7% (GetResponse 2017, p. 27). These numbers are nearly identical to our control condition. Taken together, it seems name-matching enhanced the effectiveness of the email campaign rather than a name-mismatch detracting.

Moreover, our research suggests that name matching encourages generosity even when the match is not coincidental. This finding stands in contrast to earlier work (e.g., Burger et al., 2004), which suggested that name-matching effects are larger when the match seems coincidental or unplanned. In contrast, we found that even overt name-matching can be effective in the absence of apparent serendipity. Furthermore, most past research on name effects and donation behavior involves secondary data (Chandler et al. 2008, Galak et al. 2011). Our research used a randomized field experiment. We also examined meaningful and costly variables, such as donation, whereas past field experiments have mostly asked participants to complete a survey (Garner 2005, Guéguen et al. 2005, Oates and Wilson 2002). Another contribution of the present research involves our analysis of ethnicity matching. No previous field experiments in this area have attempted to control for this potential confound.

Future work could explore the ability to repeat the results after donors have been exposed to this type of ad campaign. While DonorsChoose has replicated the result, they always ran the campaign on donors who had not been exposed to a similar campaign in the past. It may be that this type of email campaign requires novelty to be effective. Other work could also explore whether this effect extends beyond the specific context. Outside of charitable giving, people may respond differently to a company or organization using their personal characteristics to persuade.

It may come as no surprise to many that people seem to favor others who are like them. But we show that even very subtle cues to identity, such as name letters, can lead to increased engagement with a charity, a claim which to this point has been somewhat contentious. And we also show that even when it may be obvious to potential donors that such identity cues are being used to persuade them, they can still be effective. Highlighting a shared identity seems to be an effective method for personalizing email marketing campaigns. More broadly, it can be effective in reducing social distance and boosting charitable giving.

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Figure 1

Example Email

DonorsChoose.org

Firstname,

Roll call!

This summer, share the love with a teacher we've handpicked just for you. Mrs. Last, a teacher in Westerly, RI needs your help to bring her classroom request, **Desk Towers To Save The Day!**, to life.

Gratefully,
The DonorsChoose.org Team

Sent by DonorsChoose.org, 134 W. 37th St, 11 Fl, NY, NY 10018 USA. DonorsChoose.org is a 501(c)(3) nonprofit in the State of NY.

Don't want to hear from us again? Update your email preferences or unsubscribe.

Follow us on:
Facebook
Twitter
Instagram

The text of an email sent to potential donors. The names have been changed to protect anonymity.

Table 1

Main Results

Measure	No Controls		Robustness Checks: Ethnicity Match		Robustness Checks: Yoked Ethnicity Match		Robustness Checks: 25^{th} Percentile Euclidean Distance	
	Control	Name Match	Control	Name Match	Control	Name Match	Control	Name Match
n	15,142	15,155	11,784	15,130	11,629	11,629	3,785	15,155
Count Opened (%)	4177 (27.6%)	5315*** (35.1%)	3271 (27.8%)	5307*** (35.1%)	3214 (27.6%)	4102*** (35.3%)	1033 (27.3%)	5315*** (35.1%)
Count Clicked Link (%)	700 (4.6%)	1040*** (6.9%)	574 (4.9%)	1038*** (6.9%)	562 (4.8%)	814*** (7.0%)	189 (5.0%)	1040*** (6.9%)
Count Clicked Link Conditional on Opening (%)	700 (16.8%)	1040*** (19.6%)	574 (17.5%)	1038* (19.6%)	562 (17.5%)	814* (19.8%)	189 (18.3%)	1044 (19.6%)
Count Made Donation (%)	12 (0.1%)	31** (0.2%)	10 (0.1%)	31* (0.2%)	10 (0.1%)	25* (0.2%)	1 (0.0%)	31* (0.2%)
Mean Donation Amount (*SD*)	$0.09 ($5.46)	$0.20** ($7.98)	$0.11 ($5.46)	$0.20* ($7.89)	$0.11 ($6.21)	$0.19* ($7.78)	$.01 ($.81)	$.20* ($7.98)

* $p < .05$; ** $p < .01$; *** $p < .001$.

Table 2

Name Letter Effects among Non Name Matching Participants

	Count Opened Email	Count Clicked Link	Count Made Donation	Mean Donation Amount (*SD*)
Non First Letter Match (n = 11033)	3036 (27.5%)	531 (4.8 %)	8 (0.1%)	$0.09 ($5.77)
First Letter Match (n = 751)	235 (31.3%)	43 (5.7%)	2 (0.3%)	$0.41 ($10.34)
	p = .025	p = .261	p = .078	p = .078
	d = .041	d = .021	d = .033	d = .075

Includes only those who match on most-likely ethnicity. Comparison p-values for counts are computed with Chi-square tests. The mean donation amount is reported untransformed and the p-value for this test is from a Mann-Whitney U. Effect size is reported as Cohen's d.

Web Appendix

Diagnosticity of Ethnicity From Name. The analysis reported in the main text does not take into account that some names signal a particular ethnicity more than others. For example, the surname Williams is about equally as common among white people (48.5%) as it is among black people (46.7%). In this example, a person named Williams is “most likely” white, as we have used the term in our descriptive statistics, but we lose much of the information about how strong an inference one could make about ethnicity from the name itself. That is, in a match of donor Williams and teacher Williams, it seems unlikely that from name alone that donor Williams could infer that she matches the ethnicity of teacher Williams. In contrast, for a name which has a higher percentage of one ethnicity such as Miller (over 85% of Millers were white in the 2000 US census), one can make much stronger inferences about teacher Miller’s ethnicity. If ethnic in-group favoritism drives the effects, among those matched on most likely ethnicity, outcomes should be more favorable when the names are more diagnostic of ethnicity than when they are less diagnostic. That is, a donor named Barajas (96% Hispanic) should be more likely to favor a teacher named Orozco (95.1% Hispanic) than he would to favor a teacher named Silva (58.3% Hispanic, but 33.7% white). To test for this possibility, we identified for each name the percentage likelihood of being of that name’s most likely ethnicity. In the case of Silva, that percentage is 58.3%. In the case of Williams, it is 48.5%. For each donor-teacher pair, we then took the lowest such percentage to use in the subsequent analysis as a measure of diagnosticity. That is, in a Barajas-Silva pair, the number would be 58.3, whereas for a Barajas-Orozco pair the number would be 95.1. Among those matched on most likely ethnicity, this number ranged from 34.62 to 99.5, $M = 76.1$, $Mdn = 75.9$. We used the lower of the two percentages because we believed this would more accurately capture the likelihood that ethnicity matching could be inferred from surnames. In reality, the donor knows his or her own ethnicity and only must infer the ethnicity of the teacher from the teacher's surname, but given the data available, we felt this was a reasonable and conservative approximation. We then checked for interactive effects by running separate OLS regressions on each of our dependent variables including condition, the diagnosticity measure just described, and the interaction of the two as predictors. We report main effects from a model including condition and diagnosticity, and interactions from a model including all three predictors. They can thus be interpreted in the same manner as a two-way ANOVA.

For opening the email, there was a significant main effect of condition $F(1, 26910) = 143.1$, $p < .001$, no main effect of diagnosticity $F < 1$, and no significant interaction $F(1, 29610) = 1.4$, $p = .236$. For clicking on the link, there was a significant main effect of condition $F(1, 26910) = 37.7$, $p < .001$, no significant effect of diagnosticity $F(1, 26910) = 1.6$, $p = .204$, and a marginal interaction $F(1, 26910) = 2.94$, $p = .086$. For donating (binary), there was a significant main effect of condition $F(1, 26910) = 4.85$, $p = .028$, no significant main effect of diagnosticity $F < 1$, and a marginal interaction $F(1, 26910) = 3.08$, $p = .079$. For the natural log-transformed donation amount, there was a significant main effect of condition $F(1, 29610) = 4.5$, $p = .033$, no effect of diagnosticity $F < 1$, and no significant interaction $F(1, 29610) = 2.7$, $p = .103$. These results suggest that among donors who are most likely to be the same ethnicity, the effect of name matching condition holds when accounting for the ethnic diagnosticity of the names. Though the interactions never reached significance, these results are suggestive that it may be possible that the ethnic diagnosticity of a surname matters more when the teacher shares a surname than when he or she does not. While this is speculative, it may be that potential donors paid greater attention to the teacher's surname when it was also their own surname, and this highlighted the effect of ethnicity matching.

Euclidean Distance as a Control for Ethnicity. One could argue that in the previously reported methods to control for ethnicity matching, by using only information about the *most* likely ethnicity for each name, we failed to utilize all of the ethnicity information available in the census data. We therefore decided to additionally calculate Euclidean distances for each name pair. Euclidean distance is a measure of the distance between the two names in multidimensional space, where smaller numbers indicate a higher likelihood of a name-pair being of the same ethnicity probability distribution. As before, this technique is limited in that it operates under uncertainty about *both* ethnicities. In reality, potential donors know their own ethnicity and only need to infer the ethnicity of the teacher from the teacher's name. However, given the data, we feel this is a reasonable approach to take. We calculated Euclidean distances for each name-pair using the formula

$$\sqrt{\sum_{i=1}^{n}(q_i - p_i)^2} \tag{1}$$

where *p* and *q* are the surnames of the potential donor and teacher respectively, and *i* refers each of the ethnicities available in the census data numbered one through six. So, for example, q_1 is the percentage likelihood that the potential donor with this particular surname is white in the census data and p_1 is the percentage likelihood that the teacher surname with whom he or she is matched is white. When the census data set did not contain both names, we substituted a Euclidean distance of 0 in the name-match condition, and a distance of 135.1 in the name-mismatch condition, the highest observed distance.

All Euclidean distances are necessarily zero in the name match condition. In the non-name match condition, they range from .13 to 135.10 (M = 40.0, SD = 40.6). The distributions of Euclidean distances are problematic for analysis for two reasons. First, there is no variance at all in Euclidean distance in the name match condition, and thus there is a high correlation with condition. Second, the distribution of Euclidean distance in the non-match condition is very far from normal. It can be described as a bi-modal distribution, where the majority of distances are close to zero, falling steadily until a second peak forms above a distance of 100.

For these reasons we analyzed the data in a reduced-form way first. We performed significance tests selecting more restrictive comparison groups. Specifically, we selected the 50^{th}, 25^{th}, and 10^{th} percentile of Euclidean distance to be used as our comparison group in the hope of comparing our name match condition to "ethnicity match" groups. As can be seen in table S1, the basic results are robust to these comparisons.

Next, we ran OLS regressions including the Euclidean distance we calculated as a predictor. The effect of condition remained significant for all variables tested (all p's < .03). The effect of Euclidean distance was only significant when "clicked" was the dependent variable.

Table S1 - Euclidean Distance Robustness

50th Percentile (Euclidean Distance ≤ 24.05)

	Opened	Clicked	Donated	Mean Donation Amount (*SD*)
Non-Match (n = 7574)	2095 (27.7%)	371 (4.9%)	4 (0.1%)	\$.09 (\$5.06)
Name Match (n = 15155)	5315 (35.1%)	1040 (6.9%)	31 (0.2%)	\$.20 (\$7.98)
	$p < .001$	$p < .001$	$p = .006$	$p = .013$

25th Percentile (Euclidean Distance ≤ 10.68)

	Opened	Clicked	Donated	Mean Donation Amount (*SD*)
Non-Match (n = 3785)	1033 (27.3%)	189 (5.0%)	1 (0.0%)	\$.01 (\$.81)
Name Match (n = 15155)	5315 (35.1%)	1040 (6.9%)	31 (0.2%)	\$.20 (\$7.98)
	$p < .001$	$p < .001$	$p = .017$	$p = .021$

10th Percentile (Euclidean Distance ≤ 4.08)

	Opened	Clicked	Donated	Mean Donation Amount (*SD*)
Non-Match (n = 1514)	413 (27.3%)	82 (5.4%)	0 (0.0%)	\$.00 (\$.00)
Name Match (n = 15155)	5315 (35.1%)	1040 (6.9%)	31 (0.2%)	\$.20 (\$7.98)
	$p < .001$	$p = .032$	$p = .078$	$p = .089$

Comparison p-values for “Opened,” “Clicked,” and “Donated” are computed with Chi-square tests. The mean donation amount is reported untransformed in the table. However, the p-value represents an ANOVA p-value on the natural-log transformed donation amount.

Name Commonness. We examined the effect of name commonness because past research has suggested that this variable may be an important moderator of the "unit relationship" described by Burger et al. (2004). Specifically, stronger unit relationships are thought to occur when circumstances are less likely; a Californian feels a relationship when she encounters a fellow Californian in Charlotte, but not when she encounters one in Los Angeles. A similar moderation could also apply to implicit egotism (Pelham et al. 2005). Specifically, people are assumed to show greater bias when the identifier is more uniquely associated with the self, as would be the case with an uncommon name.

We tested this hypothesis in two ways. First we used the frequency with which a name endogenously appeared in the data set. Second, we appended data from the 2000 US census which has exogenous population-level name frequency data. Both name frequency variables were heavily right-skewed, meaning most names had low frequency, but a few names were very common. We therefore conducted the analysis using natural log transformations. Note that in the analyses which follow we chose to run OLS regressions instead of logit or probit regressions when the dependent variables were binary due difficulties in interpreting interactions in those analyses and following current recommendations (Ai and Norton 2003). The results of these analyses appear in the table S2. The effect of condition held in all models tested, $p < .04$. There was a significant interaction effect, as would be predicted by past findings on implicit egotism, only on the likelihood of clicking the link in the email.

Because name-letter effects are generally thought to be driven by "implicit egotism" (Pelham et al. 2005), we also tested for an interaction of name commonness and surname first-letter matching condition within the name-mismatch condition. We predicted that there should be an effect of name commonness when a potential donor and a teacher shared a first-letter, but not otherwise. The results of this analysis are presented in table S3. We observed the predicted interaction for the likelihood of donating and the donation amount.

Table S2

Name Commonness Regressions

	Opened			Clicked			Donated			Amount (LN Transformation)		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Condition	0.075*** (0.005)	0.075*** (0.005)	0.084*** (0.011)	0.022*** (0.003)	0.022*** (0.003)	0.048*** (0.006)	0.001** (0.000)	0.001** (0.000)	0.002* (0.001)	0.005** (0.002)	0.005** (0.002)	0.008* (0.004)
Natural-log of Name Frequency		-0.004 (0.002)	-0.002 (0.003)		-0.003*** (0.001)	0.002 (0.001)		0.000** (0.000)	0.000 (0.000)		-0.002** (0.001)	-0.001 (0.001)
Condition X Natural-log of Name Frequency			-0.003 (0.004)			-0.009*** (.002)			0.000 (0.000)			-0.001 (0.001)

	Opened			Clicked			Donated			Amount (LN Transformation)		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Condition	0.075*** (0.005)	0.075*** (0.005)	0.085*** (0.011)	0.022*** (0.003)	0.022*** (0.003)	0.049*** (0.006)	0.001** (0.000)	0.001** (0.000)	0.002* (0.001)	0.005** (0.002)	0.005** (0.002)	0.008* (0.004)
Natural-log of Population Frequency (Census)		-0.003† (0.002)	-0.001 (0.002)		-0.003*** (0.001)	0.001 (0.001)		0.000** (0.000)	0.000 (0.000)		-0.002*** (0.001)	-0.001* (0.001)
Condition X Natural-log of Population Frequency (Census)			-0.003 (0.003)			-0.008*** (0.002)			0.000 (0.000)			-0.001 (0.001)

Unstandardized coefficients and (standard errors) for name commonness regressions: endogenous (top panel) and exogenous (bottom panel). † $p < .1$; * $p < .05$; ** $p < .01$; *** $p < .001$.

Table S3

Name Commonness Regressions on Surname First-Letters

	Opened			**Clicked**			**Donated**			**Amount (LN Transformation)**		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
First Letter Match Condition	0.038* (0.017)	0.038* (0.017)	0.041 (0.036)	0.009 (0.008)	0.009 (0.008)	0.003 (0.017)	0.002† (0.001)	0.002† (0.001)	0.008** (0.002)	0.009* (0.005)	0.009* (0.005)	0.034*** (0.010)
Natural-log of Name Frequency		-0.002 (0.003)	-0.002 (0.003)		0.003* (0.001)	0.002† (0.001)		0.000 (0.000)	0.000 (0.000)		-0.001* (0.001)	-0.001 (0.001)
Condition X Natural-log of Name Frequency			-0.001 (0.011)			0.002 (0.005)			-0.002** (0.001)			-0.009** (0.003)

	Opened			**Clicked**			**Donated**			**Amount (LN Transformation)**		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
First Letter Match Condition	0.038* (0.017)	0.038* (0.017)	0.028 (0.035)	0.009 (0.008)	0.009 (0.008)	0.004 (0.017)	0.002† (0.001)	0.002† (0.001)	0.009*** (0.002)	0.009* (0.005)	0.009* (0.005)	0.040*** (0.010)
Natural-log of Population Frequency (Census)		-0.001 (0.002)	-0.001 (0.002)		0.002* (0.001)	0.002† (0.001)		0.000 (0.000)	0.000 (0.000)		-0.001* (0.001)	-0.001 (0.001)
Condition X Natural-log of Population Frequency (Census)			0.003 (0.010)			0.002 (0.005)			-0.002** (0.001)			-0.010*** (0.003)

Unstandardized coefficients and (standard errors) for surname first-letter name commonness regressions: endogenous (top panel) and exogenous (bottom panel). † $p < .1$; * $p < .05$; ** $p < .01$; *** $p < .001$.