Name Similarity Encourages Generosity: A Field Experiment in Email Personalization

Kurt Munz, Minah Jung, and Adam Alter

New York University

In a randomized field experiment with the education charitable giving platform DonorsChoose.org (N = 30,297), we examined email personalization using a potential donor's name. We quantified the effectiveness of matching potential donors to specific teachers in need based on surname, surname initial letters, gender, ethnicity, and surname country of origin. Full surname matching was most effective, with potential donors being more likely to open an email, click on a link in the email, and make a donation to a teacher who shared their own surname. They also donated more money overall. 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. Potential donors who shared a surname first letter but not an entire name with teachers also behaved more generously. We discuss how using a person's name in marketing communications may gain consumers' attention and reduce the social distance between them and a name-matched entity. This process may benefit the firm when consumers' existing attitudes toward the entity are favorable, but may backfire when consumers would prefer not to be associated with it.

Keywords: field experiment, charitable giving, individual targeting, personalization, one-to-one marketing

1. Introduction

During Coca-Cola's "Share a Coke" campaign, consumers could open their email to find an image of a coke bottle literally with their name on it. The emails were part of a broader name-personalization marketing campaign that saw sales rise 2.5% as category sales declined (Esterl 2014). The campaign fit with the growing trend for marketers to target communications with increasing granularity (Ansari and Mela 2003, Khan et al. 2009). Today 77% of US marketers report personalizing email messages to target individual consumers (Evergage 2018). And for good reason—recent evidence suggests that using a consumer's name in an email subject line can positively impact marketing-relevant outcomes (Sahni et al. 2018), and a sizeable majority of consumers today report being comfortable sharing their first name with marketers (King 2018). Similar tactics are also being employed in the nonprofit sector, with charities personalizing email contents by name (Ratcliff 2015) and tailoring messages to foster in-group connections (Sudhir et al. 2016).

In this paper, we focus on the context of charitable donations and ask how marketers can effectively use consumers' names to encourage engagement and generosity. In an email field experiment with DonorsChoose.org, a large charitable giving platform that raises funds for classroom projects for primary and secondary public schoolteachers, we explored whether matching a teacher in need with a potential donor by name can encourage donations. Specifically, we sent emails to potential donors to request they donate to support a particular teacher's classroom project. We randomly assigned whether or not the surname of the teacher requesting funds for the project matched the surname of the email recipient. 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. A primary goal of this paper is to quantify the magnitude of the effectiveness of various components of matching. We systematically varied whether a teacher and a potential donor shared a surname, and we measured other characteristics that can be inferred from the name including gender, ethnicity, and the country of origin of the surname. We also tested whether other measures of similarity, such as sharing only name initial letters can have an effect.

To preview our findings, matching a person in need with a donor by surname appears to be an effective individual-level marketing personalization strategy. We found significant positive effects for open rates, clicks, donation likelihood, and average donations. These effects occurred above-and-beyond matching on ethnicity or national origin. Matching a person's name was effective in gaining a potential donor's attention, with an effect size about seven times larger than ethnicity matching on open and click rates. However, name matching seemed to increase donations about the same amount as matching on ethnicity, suggesting that both may foster generosity. In contrast, matching on gender yielded a small negative effect on open rates. That is, people were slightly more likely to open an email about a teacher of the opposite gender, perhaps because opposite genders attract more attention. We also found a small effect for initial-letter matching: people tend to be more generous toward others whose surnames have the same initial letter as their own. Overall, this pattern of results seems consistent with two processes: one that relies on attention, and another centered on feelings of closeness to a similar other.

In the following sections we first briefly review the literature on personalization in a marketing context, before focusing more specifically on names and similarity. We then describe how the current study fits into this broader context and aspects that make it unique. We then report our experimental procedure and empirical results. We conclude with a discussion of our findings, provide a framework for understanding our results in the context of the existing literature, and suggest avenues for further exploration.

2. Background Literature

2.1 Personalization in Marketing

Personalization involves tailoring marketing communications using knowledge about an individual recipient. It can be as simple as addressing a consumer by name in an email subject line (Sahni et al. 2018) or email salutation (Wattal et al. 2012), but there are also more sophisticated forms of personalization. These often involve segmenting the market to finer levels of granularity, and differentially communicating with those segments (Ansari and Mela 2003). Often this involves changing the content of the message to more closely match the target segment. For example, in the context of a financial lender's direct mail campaign advertising a loan, Bertrand et al. (2010) conducted a field experiment manipulating whether or not the mail recipient matched the gender and ethnicity of a photographed person in the ad. Surprisingly, these treatments did not have significant effects, finding instead that including a photo of an attractive woman was more effective. In contrast, in the context of charitable giving, Sudhir et al. (2016) found a significant positive effect for matching recipient characteristics, observing a 42% increase in donation rate and 77% more donations when a person in the appeal was from the same religious group as the recipient.

Personalization can also mean tailoring the offering itself to better match the preferences of the recipient (Murthi and Sarkar 2003, Simonson 2005). While this is a component of targeting in general, some have suggested that personalization implies overtly communicating to a consumer that he or she has been targeted—making it clear that the options were curated at an individual level (Anand and Shachar 2009, c.f. Wattal et al. 2012). While responses can vary by culture (Kramer et al. 2007), personalizing product offerings usually has a positive effect from the perspective of the firm (Tam and Ho 2006).

Others have explored personalizing based on a consumer's past behavior (Rossi et al. 1996, Zhang 2011). For example, consumers tend to engage more with web sites (Goldfarb and Tucker 2010, Hauser et al. 2009) and banner ads (Urban et al. 2014) that automatically adjust to match their interests and cognitive styles as inferred from their recent clicks. Furthermore, retargeting, where a firm displays ads or website content highlighting a recently researched product also can be effective in some circumstances (Bleier and Eisenbeiss 2015, Lambrecht and Tucker 2013).

Despite many documented positive benefits of personalizing marketing appeals, there may be circumstances where it can detract from the firm's aims. For example, consumers may express concerns regarding their privacy (Awad and Krishnan 2006, Song et al. 2016, White et al. 2008, Zhu et al. 2017). While name-personalized email subject lines can be effective in garnering attention (Sahni et al. 2018), Wattal et al. (2012) found that name-personalized email greetings led to *lower* response rates in their data, citing concerns about privacy. Importantly however, the authors observed that familiarity with a firm (a distributor of a variety of products including long distance phone services, cellular plans, and mortgages) led to less negative responses to the name greeting.

The issue of privacy has also been studied in the context of social networks. In a field experiment on Facebook, Tucker (2014) found that consumers responded more favorably to personalized ads when they felt more in control of their personal data. The author argued that feelings of control reduced reactance (negative feelings from a situation being against one's will) and associated active countering (White et al. 2008), allowing the ads to be more effective.

2.2 Personalization by Name and Similarity

Personalization using a target consumer's name may enhance marketing engagement for many reasons. To begin, people pay special attention to their own name (Cherry 1953). Indeed, Sahni et al. (2018) point to the role of attention as one reason why email subject lines incorporating names led to positive downstream consequences for marketers in their field experiments. People also seem to simply like their own names. Some have called this a form of egotism (Jones et al. 2004, Pelham and Carvallo 2015), and have extended the idea to include liking for the initial letters of their own name beyond the level of conscious awareness (Nuttin 1985). These types of effects have been observed in charitable giving, with donors giving more to aid victims of hurricanes when the name of the storm shared the initial letters of their own name (Chandler et al. 2008). Laboratory evidence also suggests that name-letters can affect brand choices (Brendl et al. 2005).

Because people only interact with others who share their names relatively rarely, some authors have suggested that a sense of serendipity or coincidence drives helping behavior (Burger et al. 2004). For example, Burger and colleagues (2004) found that experimental participants were more likely to donate to a charity when a representative of the charity shared their given (first) name and asked for donations in person. However, compared to a control group, participants were not more likely to donate to a same-name person in need depicted in printed promotional materials. The authors concluded that the coincidence of meeting a person with the same name led to positive feelings which enhanced the relationship, a process absent when the person in need was not physically present (Burger et al. 2004). Social pressure may also contribute in the case of in-person solicitation (DellaVigna et al. 2012).

Some authors have argued that sharing a surname with someone activates predisposed evolutionary motives toward kin care (Oates and Wilson 2002). The authors claimed that sharing a surname led people to treat same-surname others more like family. However, this argument may not explain the similar findings for given names (e.g. Burger et al. 2004).

Sharing a name with someone also may make him or her seem more self-similar. People tend to like others who are similar to themselves (Byrne 1971). Sharing a name may also signal membership in a social group, and there has been wide documentation of preferential treatment toward one's own group members (Tajfel and Turner 1979). Furthermore, our group members and people who are close to us (either as family members or friends) tend to also be similar to us (e.g. Goel and Goldstein 2013), and since we tend to donate more to personally relevant charities such as those that target the illnesses of our friends and loved ones (Small and Simonsohn 2008), we tend to donate more to those who are similar to us. 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.

3. The Current Study

In the current research, we follow the example of Sudhir et al. (2016) in quantifying effect sizes and economic relevance of manipulations derived from behavioral theories in a field setting. While marketing communications using consumers' personal data (such as their names) have garnered mixed results in the literature, we predict positive effects in the present experiment because secondary data analyses in related contexts, such as peer micro-lending

(Galak et al. 2011) and donations to the Red Cross (Chandler et al. 2008) have documented positive correlations. However, in those studies there were no active persuasion attempts—marketers were not using a consumer's information to persuade them. Consumers may react very differently when they believe a marketer is trying to persuade them (Campbell and Kirmani 2000, Friestad and Wright 1994), and may actively resist (White et al. 2008). A field experiment would thus enable stronger claims as to the causal nature of similarity in affecting charitable giving. Can a marketer use similarity to persuade, or do benefits only accrue under conditions of self-selection? If so, which elements are most effective for marketers to manipulate?

We also predict positive effects for communications mediated by a third party. That is, we expect our manipulation to be effective despite the email sender (DonorsChoose) not being the actual party in need (the teacher). Past work has cast doubt on this possibility, suggesting that the effect relies on a requester forming a personal relationship with the donor (Burger et al. 2004).

Our research makes several contributions to the literature. First, we contribute to understanding the effects of personalization in marketing. While there have been somewhat mixed results in terms of the effectiveness of personalizing marketing communications (Bertrand et al. 2010, Wattal et al. 2012, White et al. 2008), we demonstrate positive effects for using a person's own name to persuade them to donate to charity. We contribute an important data point to understanding when personalization helps the firm (Sahni et al. 2018, Sudhir et al. 2016) and when it may hurt (Wattal et al. 2012, White et al. 2008). Toward this end, we reconcile our findings with the existing literature to propose a new framework for understanding the boundary conditions for personalization.

Second, following Sudhir et al. (2016), we quantify effect sizes and economic relevance of manipulations derived from behavioral theories in a field setting. In doing so, we report a highly powered, ecologically valid experiment to test the hypothesis that people are more generous towards similar others (Loewenstein and Small 2007). The existing evidence for this hypothesis in the context of charity has come from secondary data (e.g. Chandler et al. 2008, Galak et al. 2011) or from smaller scale experiments (Burger et al. 2004, Guéguen et al. 2005, Oates and Wilson 2002). Our randomized field experiment helps establish causality and provides evidence that marketers can use these principles to increase charitable giving at scale. Furthermore, we quantify which aspects of similarity based on name are more and less effective. Marketers in other contexts may be able to use these insights when matching an offering to a consumer by name is practically infeasible.

Finally, we contribute to understanding the underlying psychological mechanisms driving the effect of similarity. While some past research has suggested that coincidental similarity fosters a positive feeling of serendipity which enhances a personal relationship between people (Burger et al. 2004), our results show that positive benefits do not rely on an encounter seeming serendipitous. Instead, our results favor two alternate explanations related to similarity capturing more attention (Sahni et al. 2018) or by making others feel socially close (Loewenstein and Small 2007). Egotism (Pelham et al. 2002), where people may extend their own positive self-associations to other people or objects that are similar, may also contribute to feelings of closeness to the self. However, real-world evidence for egotism has been recently debated. Some researchers have claimed egotism applies even to the initial letters of one's name, and can influence major life decisions such as whom to marry (Jones et al. 2004) and where to work (Anseel and Duyck 2008). However, these findings were based on secondary data, and have been contested based on alternate explanations (Simonsohn 2011a, b). In our control condition, we find evidence for a surname initial letter effect. Because of random assignment and additional controls, our design reduces the likelihood that alternate explanations drive the observed effects.

4. 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]

4.1 Participants and Random Assignment

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. Our randomization procedure involved three steps. Figure 1 outlines the procedure.

First, we randomly reduced the size of the list so that every teacher could be matched with two potential donors. This allowed us to use each teacher (and his or her proposed project) as a stimulus in *both* conditions exactly once, a type of yoked design. Specifically, potential donors were randomly assigned to condition, and each teacher-project was seen by one potential donor in *each* condition. This design also prevented 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 randomly reduced the number of donors in most

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

cases (whenever the number of donors with a particular surname was greater than twice the number of teachers with the same name), and randomly reduced the number of teachers in others (whenever the number of donors was less than twice the number of teachers). 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. Panel 1 of figure 1 provides additional examples. This procedure left us with a sample of 15,370 teachers/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).

Second, we randomly assigned participants to one of two conditions. This is depicted in panel 2 of figure 1. Half the participants with a surname were randomly assigned to a name-match condition, and the other half with that surname were randomly assigned to a name-mismatch condition.

Third, we randomly shuffled the donors in the name-mismatch condition to ensure that no donor matched the surname of the teacher he or she would read about. This is depicted in panel 3 of figure 1. Thus, in the name-match condition the donor and teacher shared a surname, and in the name-mismatch condition the donor and teacher did not share a surname.

4.2 Procedure

Each participant 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 2.

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.

5. Results

5.1 Name-Matching

As summarized in table 1, we first we report the results of the name-matching manipulation without attempting to control for other variables. 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 $F(1, 30295) = 8.02$, $p = .005$, $d = .016$. There was no significant difference in donation amount between the conditions, conditional on making a donation. That is, the average amount donated (among only those who donated) was about the same in both groups. To summarize, these results indicate that matching a donor to a teacher with the same surname improved all of the outcomes we measured.[2]

5.2 Inferring Gender, Ethnicity and Origin Country From Name

One of the primary goals of this paper is to quantify the effect size for various components of matching. Beyond exact surname matches, teachers and donors could potentially match on gender, ethnicity, or national origin. We discuss structural features of the name itself such as initial letters in a later section. The data provided by DonorsChoose did not contain demographic information regarding ethnicity or national origin, but did contain gender information for teachers (only). However, because ethnic and national origin may be inferable from a surname (Simonsohn 2011a), it was important to control for them in our analysis to the greatest extent possible. We also aimed to compare the effectiveness of matching on these

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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 $F(1, 29896) = 8.9$, $p = .003$.

characteristics. Can a marketer achieve similar results to name matching by matching on ethnic origin, for example?

We attempted this analysis using two methods. First, we partnered with a third-party company that classified gender, ethnicity, and national origins of names using a machine-learning algorithm trained on large data sets. Second, we appended US Census data for each surname regarding the most likely ethnicity for each surname. The effect of name-matching held when controlling for these other variables using both methods, and the analysis of effect sizes was similar. In the next sections we report the specific analyses for both methods.

5.2.1 Machine Learning Approach

We partnered with Namsor, a company that classifies names by gender, ethnicity, and national origin based on a proprietary machine-learning algorithm. Namsor trained their algorithm using data sets from across the world, and claims accuracy of about 75% for ethnicity in the US and greater than 95% for gender. We provided Namsor with both the given name and surname for each donor and teacher in our sample. Providing both names aids classification accuracy. For example, according to Census data, many surnames in the US are about equally common between two ethnicities. If a given name is more closely associated with one of those ethnicities, it can be used to reduce the uncertainty of the classification. A similar idea applies to gender. For example, Karen Gallagher is likely to be a female Irish name, while Karen Petrossian is more likely to be a male Armenian name.

Using this approach, 18488 (61.0%) donors' names were classified as white, 6820 (22.5%) black, 2888 (9.5%) Hispanic, 972 (3.2%) Asian, and 1129 (3.7%) were not classified.[3]

[3] Names were not classified if the algorithm had not learned them prior. This was most often the case when only an initial was used in place of either a given name or surname.

The distribution of ethnicities for teachers' names was about the same, as intended by our experimental design.

For gender, 22242 (73.4%) of the donors' names were classified as female, 6494 (21.4%) as male, 1082 (3.6%) as unknown, and 478 (1.6%) were not classified. Teachers' names were classified female 87.5% of the time, with 10.8% male, and 3.5% unknown.[4] The DonorsChoose data contained gender information about teachers in the form of a prefix: Mrs., Ms., Mr., or Teacher. Assuming that "Mr." is male and "Mrs." or "Ms." is female, we inferred that 89.7% of teachers were female, 8.1% male, and 2.2% unknown. The gender classified by the algorithm agreed with the gender inferred from the prefix 91.7% of the time overall and 96.9% of the time when both methods classified an actual gender (rather than "Teacher"), approximating our expectations a priori. See the web appendix for additional descriptive details.

With these additional data about ethnicity and gender appended to our original data set, we conducted OLS regressions on each of our dependent measures. Even though several of our dependent measures were binary, we chose to use OLS regressions because recent work has pointed to problems in interpreting interaction terms in regression methods more commonly used for binary data such as Probit and Logit regressions (Ai and Norton 2003). Results are presented in tables 2 through 5, with each table presenting a unique dependent variable: open (yes/no), click (yes/no), donate (yes/no), and donation amount (natural log transformation). Each table depicts OLS regression results for four model specifications with increasing levels of specificity regarding ethnicity. Each table includes all potential donors. That is, none of these tables depict conditional effects, such as clicking behavior for only those who opened the email. Matching on

[4] Less than 1% of names were not classified; the data set contained higher fidelity name data for teachers than donors.

specific country of origin of a name did not yield a significant effect in any model we tested, and we therefore do not discuss it further.

Open Rate. Participants opened 9,492 of the emails we sent overall (31.3%). As reported in table 2, being randomly assigned to the name-match condition was associated with an increase in open rates of seven percentage points compared to the model intercept of 26.2%. In contrast, matching on gender was associated with a *decrease* in open rates of about 1.5 percentage points, though this estimate did not reach the traditional threshold for significance. Matching on ethnicity was not significantly associated with a change in open rate, though overall model estimates were consistent with the idea that matching on this criterion boosted engagement (model 1). However, much of the positive effect of ethnicity matching may have been driven by matches among those with Asian names (model 4), facilitating open rate improvements of about 8.3 percentage points. Note, however, that given the small number of Asian names in the sample (972; 3.2%), this finding was not reliable at traditional levels of significance. While not predicted a priori, we also observed that females were significantly more likely to open the email from DonorsChoose, all else equal.

Click Rate. Table 3 reports similar results for clicking the link in the email. Again the effect of name-matching held in all models. Overall 1,740 potential donors clicked on the link in the email (5.7% of all potential donors; 18.3% of those who opened the email). The analysis in table 3 includes all potential donors. From an intercept of 3.5%, the name match manipulation was associated with an increase in click rate of about 2 percentage points. The effect of matching on ethnicity appeared to differ by ethnicity (model 4). When both the names of the potential donor and the teacher were categorized as white, matching on race was associated with a 1.4 percentage point increase in clicks, whereas a match of two names categorized as black was associated with a decrease of 2.9 percentage points. Matching on gender was not associated with a reliable effect on click rates.

Donation Behavior. Overall the campaign received 43 donations (31 in the name-match condition). Table 4 depicts the results of an OLS regression on donation behavior including all potential donors. Model 1 shows that while donation rates were overall low, being in the name-match condition was associated with a significantly higher incidence of donating. Similarly, matching on ethnicity was also independently associated with a significantly higher incidence of donating, about equal in magnitude to name-matching. Matching on gender did not significantly affect donation behavior, but unexpectedly males were more likely to donate than females.

Donation Amount. In table 5, we depict the results of a regression on donation amounts. We included those who did not donate as zeroes in this analysis, which yielded a rather skewed distribution. We therefore conducted a natural log transformation on the donation amount prior to analysis. Similar to binary (yes/no) donation behaviors, this analysis revealed a significant positive effect for both name matching and ethnicity matching. There was no effect of matching on gender, but overall males donated more on average.

5.2.2 Census Approach

We also 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.[5] We appended these percentages to our data for both the potential donor's surname and the corresponding teacher's surname.

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[5] 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. This approach has the advantage of making inferences from the surname itself, a process that conceptually matches the actual process being used by the donors. Using this classification method, 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.

There seems to be a rather large discrepancy when categorizing ethnicity between using the machine learning approach and the Census approach. Much of this difference may be due to some surnames being ambiguous with respect to ethnicity. For example, in the Census, the surname Williams is about equally as common among white people (48.5%) as it is among black people (46.7%). With the current approach, a person named Williams is "most likely" white. However, the machine learning approach also used given names to help categorize a name, greatly improving accuracy. Because many names are common between ethnicities, but are overall more common among white people, the census method probably over-categorized names as white.

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 designed.

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. 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 $F(1, 26912) = 5.8$, $p = .016$. 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.[6] We report regression tables similar to those seen in the previous section, in the web appendix. The conclusions are largely consistent between methods for identifying ethnicity.

5.3 Name-Letter Effects

Donors and teachers may match on structural features of their names such as initial letters. Because people tend to like the letters of the their name more than other letters (Nuttin 1985), they may also be more generous toward those who share name initial letters (Galak et al. 2011). This may be a form of egotism in that people generally have positive self-evaluations and may transfer those evaluations to entities that remind them of themselves (Jones et al. 2004, Pelham et al. 2002). Some have claimed that these processes affect major life decisions, such as where to work (Anseel and Duyck 2008) and whom to marry (Jones et al. 2004, Pelham and Carvallo 2015). However, studies claiming to have documented real-world effects relied on secondary data, and skeptics have questioned their reliability on empirical grounds, arguing that the observed relationships may have resulted from reverse causality (e.g. people naming businesses after themselves rather than choosing to work at businesses with their name-letters) or third-variable explanations (e.g. favoring ethnic groups) (Simonsohn 2011a, b). Thus, a randomized experiment may go far in alleviating some of the concerns.

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[6] 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 $F(1, 23256) = 5.8$, $p = .016$.

We tested for surname initial-letter effects within our name-mismatch (control) condition. By chance, 932 of the name-mismatched pairs shared the same first letter. No one in this group matched on full-surname, nor could the name-letter matches be the result of reverse causality. We also controlled for ethnicity using the control variables inferred from the machine-learning approach discussed previously. We present the results of this analysis in table 6. We find significant name-letter effects when opening the email (yes/no) was the dependent variable, and directionally consistent effects on all other dependent variables. The results are consistent if we instead use the census data, and examine only those who match on most likely ethnicity.[7]

5.4 Name Commonness

Do people with less common names react more favorably to seeing their names in email marketing? Psychological accounts explaining the effects of similarity that rely on serendipity (Burger et al. 2004) or egotism (Jones et al. 2002) predict that they should. If the pleasant surprise of coincidence drives the effect, matching uncommon names should be more surprising (Burger et al. 2004). Similarly, people may have stronger ego reactions to entities more uniquely tied to the self, such as uncommon names (Jones et al. 2002). 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.

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[7] 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 $\chi^2(1, N = 11{,}784) = 1.3$, $p = .261$, $d = .021$.

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 may make sense given our design: there was no pretense of the full name-match being coincidental, and thus it is likely some other process 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 (Jones et al. 2004, Pelham et al. 2002). Consistent with this explanation, we did observe this interaction on the likelihood of donation and the amount donated. The full analysis is reported in the web appendix.

6. Discussion and Conclusion

In this section, we discuss the conclusions we can draw from our results, with a particular focus on guiding marketing managers to apply them. We open by discussing the overall effectiveness of manipulating similarity related to names, suggesting that personalizing along these dimensions benefitted the firm, rather than "badly executed personalization" disenchanting consumers. Next, we discuss the potential psychological processes that are supported by the data. We do so in order to propose a framework that may integrate past findings in marketing personalization to better understand the boundary conditions for when personalization may or may not benefit the marketer's aims. We also suggest avenues for future research that could test the framework, and other related questions that may be interesting to both academics and practitioners.

6.1 Effectiveness

Did highlighting name similarity enhance engagement with the DonorsChoose email campaign? On first pass, the answer seems obvious. Potential donors were more likely to open the email, click, donate, and they donated more on average to teachers who shared their surname compared to a control group. However, in a two-group design such as this one, it is possible that the control group may have revealed a negative effect rather than the treatment group benefitting. Specifically, if teachers supposedly "handpicked" for potential donors were actually poorly matched with their interests, it may have caused negative reactions. These reactions could have been stronger in the control group where the matching was done randomly and without apparent reason. The question highlights an important consideration for marketers. Does badly executed personalization hurt the firm?

In our data, the email campaign seemed to be 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. 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.

Accordingly, DonorsChoose has been motivated to subsequently apply the lessons learned from this experiment to replicate its success in eliciting donations on numerous occasions.[8] While they no longer use a control group, they have observed similar levels of

[8] The experiment we report 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

engagement and donation on subsequent iterations of what has become an annual campaign tied to the Valentine's Day holiday. A typical email reads, "Roses are red, Violets are blue, Give to a teacher with the same name as you." DonorsChoose has successfully used name matching to raise thousands of dollars, and has 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. This provides more evidence that marketers can actively use a person's name or identity to persuade. That is, the match does not need to seem serendipitous (Burger et al. 2004), nor is the effect limited to conditions of self selection (Chandler et al. 2008, Galak et al. 2011).

Beyond full name matches, we have also demonstrated that matching on more practical measures can also boost outcomes. We observed positive effects on open rates from mere surname initial letter matching, and matching on ethnicity had an effect similar in magnitude to name matching for donations. Matching on these dimensions may be easier to implement in marketing communications. For example, charity marketers could match the ethnicity of a photographed model to that of the sender or for-profit firms could recommend brands that begin with name letters (Brendl et al. 2005). Importantly, however, matching on these dimensions seems to affect certain outcomes differently than others. In the next section, we discuss how this variation may have implications for understanding the psychological process.

6.2 Psychological Process and Implications for Personalization in Marketing

The results also may help to understand the psychological processes underlying similarity-based helping behavior. Scholars have proposed several accounts for why people

not report the results of that experiment here. None of the participants from the first experiment participated in our reported experiment.

behave more charitably when they encounter self-similar entities. Some have suggested that people feel good when they serendipitously encounter someone of the same name, and these positive feelings enhance in-person relationships (Burger et al. 2004). Others have suggested that people are predisposed by evolution to treat same-surname others as if family (Oates and Wilson 2002). Because we find effects over email without an in-person relationship, even occurring at the level of name initial letters, these explanations seem less likely to have large effects in the present research. In contrast, two other accounts seem more likely. First, people may simply pay greater attention to self-similar stimuli, leading to positive downstream consequences (Sahni et al. 2018). Second, similarity may decrease the social distance between people (Loewenstein and Small 2007), treating others like members of the same social group (Sudhir et al. 2016) and leading to more charitable behavior (Galak et al. 2011). In addition to group-favoritism, egotism may also play a role—people like themselves and therefore also tend to like things that remind them of themselves, even if they are not consciously aware of the cause (Jones et al. 2004, Pelham et al. 2002, Pelham and Carvallo 2015, c.f. Simonsohn 2011a, b). Our data provide support for these processes.

Consistent with the idea that names garner attention (Sahni et al. 2018), we find that emails with name-matched subject lines are opened more often. We also find small *negative* effects for similarity on gender (donors tend to open emails more often when the subject teacher is the opposite gender). As opposite genders attract greater attention (Maner et al. 2007), this result is also consistent with an attention mechanism. It is consistent with past field experiments where attractive women led to better responses in a direct mail campaign (Bertrand et al. 2010), but contrasts a study on secondary data where same-genders encouraged micro loans to would-be entrepreneurs (Galak et al. 2011). The difference may be due to context. Specifically, if attention drives engagement, its effect may only be detectable under circumstances of low baseline attention, such as a solicitation attempt by mail or email (this study, Bertrand et al. 2010). In contrast, under conditions of self-selection, such as when people choose to browse profiles on a micro-lending platform (Galak et al. 2011), all observed parties are already attentive, and other processes may dominate.

Furthermore, our results are also consistent with ideas about social distance and egotism. Specifically, we observed effects for full surname matches, surname initial letter matches, and ethnicity matches. Both theories predict these results. Additionally, we found some limited evidence that the effect is stronger for less common names, a direct prediction from an egotism theory (Jones et al. 2002). Comparing across dependent variables may also suggest that ethnicity matching may be relatively more impactful on actual donations, rather than open or click rates. When potential donors click on a link in the email, they are brought to a project page on the DonorsChoose.org web site, which often contains a small photo of the teacher requesting funds. It may be that ethnicity matching is more powerful when visually apparent, rather than inferred from a surname.

Considering egotism and social distance may also help us to hypothesize about when personalizing using similarity might help drive engagement with marketing communications (Sahni et al. 2018, Sudhir et al. 2016), and when it might be less effective or even backfire (Wattal et al. 2012). While the effect of similarity generally leads to positive outcomes, people may respond differently to self-similar entities under threatening conditions (Brendl et al. 2005, Jones et al. 2002), or when the self-similar entity is otherwise undesirable (e.g. Alter 2009). For instance, a study by Burger and colleagues (2004) found that when a person in a photograph shared a name with a potential donor, there was no boost in donations. One possible explanation could be that the photographed person in that case was afflicted with Cystic Fibrosis, a life-threatening condition that severely degrades lung functioning. It is possible that people felt threatened or were uncomfortable with their name being associated with the illness. A similar logic may apply to the results reported by Wattal et al. (2012), who found that email recipients responded negatively when a firm addressed them by their given name. The firm sending the email in that study was a distributor of long distance telephone service and other utilities. If consumers held negative associations with the firm or the category, they may have reacted negatively to such a company attempting to reduce the social distance between them. In contrast, when consumers had positive existing associations, such as when the sender was a company that helps prepare for career milestones, a company with whom consumers had already transacted, or a prestigious university (Sahni et al. 2018), or when the party in need of help was a healthful older person fallen on financial hard times (Sudhir et al. 2016), highlighting similarity was better received. This seems also to be the case in the present study.

In summary, we are proposing that highlighting similarity, be it through names (Chandler et al. 2008, Galak et al. 2011, Sahni et al. 2018, Wattal et al. 2012) or social group membership (Bertrand et al. 2010, Sudhir et al. 2016), does seem to decrease the social distance between people. How people respond may depend on whether or not they wish to be more closely associated.

6.3 Future Directions

Future work should directly test the framework proposed in the previous section, as alternate explanations may also play a role. For example, consumer reactions may change over time. If consumers become accustomed to marketers using their names (King 2018), doing so may trigger fewer concerns over privacy (Song et al. 2016, Wattal et al. 2012), allowing the positive effects on attention to be more pronounced. This could explain why older findings seem to be more negative (Wattal et al. 2012, White et al. 2008) than more recent ones (Sahni et al. 2018). However, we prefer our proposed framework because it can additionally account for the pattern of results observed by Burger and colleagues (2004).

Future work could also 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, particularly when attempting to garner attention.

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. However, the recent work by Sahni et al. (2018) finding positive effects by for-profit firms using names in email subject lines should encourage optimism.

6.4 Conclusion

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, which also independently seems to enhance donation behavior. We also demonstrated a very small name-letter effect in our name-mismatch condition when controlling for ethnicity. 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 controlling for ethnicity and without the possibility of the effect being driven by full-name matches, we believe this provides the most unbiased test of name-letter effects 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.

We also quantified the effects of various components of matching to better understand if and how marketers might effectively use them in their persuasive communications. Use of full names and emails about people of the opposite gender may garner greater attention, while similarity by name and ethnicity may foster increased charitable giving.

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

	Teachers	Donors
Brown	122	~~379~~ 244
Johnson	166	~~490~~ 332
Naranjo	1	2
Ortiz	~~15~~ 12	~~25~~ 24
Smith	217	~~660~~ 434
Walsh	~~17~~ 15	30
Zimmer	~~3~~ 1	~~3~~ 2

1. Reduce initial list size to achieve exact 2:1 donor to teacher ratio.

If number of donors > 2x number of teachers (most frequent), randomly eliminate donors (e.g. Smith).

If number of donors < 2x number of teachers, randomly eliminate teachers (e.g. Walsh).

Name Match		Name-Mismatch	
Teacher	Potential Donor	Teacher	Potential Donor
Smith$_{1}$	Smith$_{A}$	Smith$_{1}$	Smith$_{B}$
Jones$_{1}$	Jones$_{B}$	Jones$_{1}$	Jones$_{A}$
Davis$_{1}$	Davis$_{B}$	Davis$_{1}$	Davis$_{A}$
White$_{1}$	White$_{A}$	White$_{1}$	White$_{B}$
Brown$_{1}$	Brown$_{B}$	Brown$_{1}$	Brown$_{A}$
Garcia$_{1}$	Garcia$_{A}$	Garcia$_{1}$	Garcia$_{B}$
Smith$_{2}$	Smith$_{C}$	Smith$_{2}$	Smith$_{D}$

2. Randomly assign potential donors to condition.

Teachers are used as stimuli once in both conditions. Each individual teacher is identified by a unique numerical subscript.

Potential donors appear once, randomly assigned to either the name match or name-mismatch condition. Each individual donor is identified by a unique letter subscript.

Name Match		Name-Mismatch	
Teacher	Potential Donor	Teacher	Potential Donor
Smith$_{1}$	Smith$_{A}$	Smith$_{1}$	Davis$_{A}$
Jones$_{1}$	Jones$_{B}$	Jones$_{1}$	White$_{B}$
Davis$_{1}$	Davis$_{B}$	Davis$_{1}$	Smith$_{D}$
White$_{1}$	White$_{A}$	White$_{1}$	Garcia$_{B}$
Brown$_{1}$	Brown$_{B}$	Brown$_{1}$	Jones$_{A}$
Garcia$_{1}$	Garcia$_{A}$	Garcia$_{1}$	Smith$_{B}$
Smith$_{2}$	Smith$_{C}$	Smith$_{2}$	Brown$_{A}$

3. Randomly shuffle donors in mismatch condition to achieve mismatch.

Each individual teacher is identified by a unique numerical subscript. Each individual donor is identified by a unique letter subscript.

Figure 2

Example Email

From: "DonorsChoose.org Team"
To: "Greg Donnelly" [name match] / "Greg Williams" [non match]
Subject: Treat Mrs. Donnelly's Classroom this Summer!

DonorsChoose.org

Greg,

Roll call!

This summer, share the love with a teacher we've handpicked just for you.
Mrs. Donnelly, a teacher in New York, NY needs your help to bring
her classroom request, **iPads for Sci Grads** 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.

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Twitter
Instagram

The text of an email sent to potential donors. In the name-match condition, the surname of the potential donor was the same as the surname of the teacher. A teacher's project was not necessarily emailed to two donors with the same given name. We used two donors named "Greg" here for simplicity of presentation.

Table 1 - Effects of Randomly Assigned Name Match Condition

Measure	Control	Name Match
n	15,142	15,155
Count Opened (%)	4177 (27.6%)	5315*** (35.1%)
Count Clicked Link (%)	700 (4.6%)	1040*** (6.9%)
Count Clicked Link Conditional on Opening (%)	700 (16.8%)	1040*** (19.6%)
Count Made Donation (%)	12 (0.1%)	31** (0.2%)
Count Made Donation Conditional on Clicking (%)	12 (1.7%)	31† (3.0%)
Mean Donation Amount (*SD*)	$0.09 ($5.46)	$0.20** ($7.98)

†= $p < .10$, * $p < .05$; ** $p < .01$; *** $p < .001$.

Table 2 – OLS Regression on Opening Email

	Model 1		Model 2		Model 3		Model 4	
	Est (SE)	*t*-stat	Est (SE)	*t*-stat	Est (SE)	*t*-stat	Est (SE)	*t*-stat
Intercept	.261 (.007)	36.79***	.262 (.008)	33.98***	.261 (.008)	31.92***	.262 (.015)	16.98***
Name Match	.070 (.006)	11.92***	.070 (.006)	11.92***	.070 (.006)	11.84***	.069 (.006)	11.49***
Ethnicity Match	.008 (.006)	1.47	.009 (.009)	1.41	.009 (.006)	1.49	.009 (.015)	.61
Female Donor	.026 (.009)	2.94**	.025 (.009)	2.86**	.025 (.009)	2.87**	.026 (.009)	2.89**
Gender Match	-.015 (.008)	-1.90†	-.014 (.008)	-1.78†	-.014 (.008)	-1.78†	-.014 (.008)	-1.78†
Country Match	.004 (.006)	.76	.004 (.006)	.68	.004 (.006)	.69	.003 (.006)	.48
Black Teacher			.000 (.007)	-.006	.000 (.007)	-.01	.003 (.015)	.23
Hispanic Teacher			-.015 (.009)	-1.61	-.016 (.010)	-1.56	-.022 (.017)	-1.33
Asian Teacher			.019 (.017)	1.15	.017 (.017)	.98	.002 (.021)	.11
Black Donor					.001 (.007)	.09	.004 (.015)	.27
Hispanic Donor					.003 (.010)	.29	-.003 (.017)	-.18
Asian Donor					.017 (.017)	.96	.002 (.022)	.10
Ethnicity Match × Black							-.012 (.030)	-.40
Ethnicity Match × Hispanic							.018 (.032)	.57
Ethnicity Match × Asian							.082 (.050)	1.65†

Unstandardized parameter estimates and (standard errors).
$^{\dagger} = p < .10$, $* = p < .05$, $** = p < .01$, $*** = p < .001$

Table 3 – OLS Regression on Clicking Link in Email

	Model 1		Model 2		Model 3		Model 4	
	Est (SE)	*t*-stat	Est (SE)	*t*-stat	Est (SE)	*t*-stat	Est (SE)	*t*-stat
Intercept	.045 (.004)	12.73***	.046 (.004)	11.98***	.044 (.004)	10.71***	.036 (.008)	4.59***
Name Match	.021 (.003)	7.25***	.022 (.003)	7.28***	.021 (.003)	7.11***	.020 (.003)	6.79***
Ethnicity Match	.003 (.003)	1.13	.003 (.003)	.90	.005 (.003)	1.46	.014 (.007)	1.89†
Female Donor	.002 (.004)	.35	.001 (.004)	.30	.001 (.004)	.33	.002 (.004)	.44
Gender Match	-.003 (.004)	-.81	-.003 (.004)	-.72	-.003 (.004)	-.76	-.004 (.004)	-.91
Country Match	.001 (.003)	.19	.001 (.003)	.21	.000 (.003)	.11	.000 (.003)	-.16
Black Teacher			-.003 (.003)	-.87	-.003 (.004)	-.85	.009 (.008)	1.15
Hispanic Teacher			-.004 (.005)	-.92	-.003 (.005)	-.58	-.002 (.008)	-.27
Asian Teacher			.008 (.008)	.98	.006 (.009)	.74	.011 (.011)	1.06
Black Donor					.005 (.004)	1.51	.017 (.008)	2.25*
Hispanic Donor					-.001 (.005)	-.21	.000 (.008)	-.03
Asian Donor					.017 (.009)	1.93†	.022 (.011)	2.04*
Ethnicity Match × Black							-.029 (.015)	-1.89†
Ethnicity Match × Hispanic							.004 (.016)	.24
Ethnicity Match × Asian							-.005 (.025)	-.20

Unstandardized parameter estimates and (standard errors).
† = $p < .10$, * = $p < .05$, ** = $p < .01$, *** = $p < .001$

Table 4 – OLS Regression on Donating (yes/no)

	Model 1		Model 2		Model 3		Model 4	
	Est (SE)	*t*-stat	Est (SE)	*t*-stat	Est (SE)	*t*-stat	Est (SE)	*t*-stat
Intercept	.0018 (.0006)	3.09***	.0023 (.0006)	3.69***	.0025 (.0007)	3.79***	-.0020 (.0012)	1.59
Name Match	.0011 (.0005)	2.26*	.0011 (.0005)	2.40*	.0012 (.0005)	2.43*	.0012 (.0005)	2.56*
Ethnicity Match	.0010 (.0005)	2.25*	.0007 (.0005)	1.41	.0006 (.0005)	1.10	.0010 (.0012)	.86
Female Donor	-.0017 (.0007)	-2.35*	-.0017 (.0007)	-2.37*	-.0017 (.0007)	-2.32*	-.0017 (.0007)	-2.31*
Gender Match	-.0001 (.0006)	-.15	-.0001 (.0006)	-.13	-.0001 (.0006)	-.12	-.0001 (.0007)	-.17
Country Match	-.0003 (.0005)	-.69	-.0003 (.0005)	-.62	-.0003 (.0005)	-.58	-.0002 (.0005)	-.40
Black Teacher			-.0011 (.0006)	-1.99*	-.0011 (.0006)	-1.93†	-.0008 (.0012)	-.69
Hispanic Teacher			-.0007 (.0008)	-.87	-.0002 (.0008)	-.24	.0006 (.0013)	.44
Asian Teacher			-.0015 (.0014)	-1.12	-.0018 (.0014)	-1.32	-.0009 (.0017)	-.52
Black Donor					-.0006 (.0006)	-1.02	-.0003 (.0012)	-.27
Hispanic Donor					-.0013 (.0008)	-1.51	-.0005 (.0013)	-.35
Asian Donor					.0012 (.0014)	.88	.0022 (.0017)	1.25
Ethnicity Match × Black							-.0003 (.0024)	-.13
Ethnicity Match × Hispanic							-.0021 (.0026)	-.81
Ethnicity Match × Asian							-.0042 (.0040)	-1.04

Unstandardized parameter estimates and (standard errors).
$^{\dagger}= p < .10$, $* = p < .05$, $** = p < .01$, $*** = p < .001$

Table 5 – OLS Regression on Natural Log Transformed Donation Amount

	Model 1		Model 2		Model 3		Model 4	
	Est (SE)	*t*-stat	Est (SE)	*t*-stat	Est (SE)	*t*-stat	Est (SE)	*t*-stat
Intercept	.0078 (.0024)	3.32**	.0101 (.0026)	3.93***	.0108 (.0027)	3.97***	.0088 (.0051)	1.73†
Name Match	.0042 (.0020)	2.17*	.0045 (.0020)	2.31*	.0046 (.0020)	2.33*	.0049 (.0020)	2.46*
Ethnicity Match	.0045 (.0019)	2.38*	.0030 (.0020)	1.51	.0026 (.0021)	1.25	.0044 (.0049)	.88
Female Donor	-.0078 (.0029)	-2.64**	-.0079 (.0029)	-2.68**	-.0077 (.0029)	-2.62**	-.0077 (.0029)	-2.62**
Gender Match	-.0002 (.0027)	-.07	-.0001 (.0027)	-.05	-.0001 (.0027)	-.04	-.0002 (.0027)	-.07
Country Match	-.0019 (.0019)	-.97	-.0017 (.0019)	-.91	-.0017 (.0019)	-.86	-.0013 (.0020)	-.68
Black Teacher			-.0047 (.0023)	-2.03*	-.0045 (.0023)	-1.94†	-.0037 (.0050)	-.75
Hispanic Teacher			-.0033 (.0031)	-1.06	-.0015 (.0034)	-.44	.0015 (.0055)	.28
Asian Teacher			-.0061 (.0056)	-1.10	-.0076 (.0057)	-1.35	-.0035 (.0070)	-.50
Black Donor					-.0023 (.0023)	-1.01	-.0016 (.0050)	-.31
Hispanic Donor					-.0049 (.0034)	-1.44	-.0019 (.0055)	-.35
Asian Donor					.0070 (.0058)	1.22	.0112 (.0072)	1.56
Ethnicity Match × Black							-.0007 (.0100)	-.07
Ethnicity Match × Hispanic							-.0079 (.0105)	-.76
Ethnicity Match × Asian							-.0192 (.0164)	-1.17

Unstandardized parameter estimates and (standard errors).
† = $p < .10$, * = $p < .05$, ** = $p < .01$, *** = $p < .001$

Table 6 – OLS Regressions Testing First Letter Effects (on Control Condition Only)

	Opened		Clicked		Donated		Ln Donation Amount	
	Est (SE)	*t*-stat	Est (SE)	*t*-stat	Est (SE)	*t*-stat	Est (SE)	*t*-stat
Intercept	.2621 (.0178)	-14.74***	.0329 (.0083)	3.95***	.0003 (.0011)	.26	.0034 (.0046)	.74
First Letter Match	.0364 (.0156)	2.34*	.0077 (.0073)	1.05	.0016 (.0010)	1.65†	.0075 (.0041)	1.84†
Ethnicity Match	-.0018 (.0173)	-.11	.0104 (.0081)	1.28	.0011 (.0011)	1.04	.0035 (.0045)	.77
Female Donor	.0345 (.0122)	2.83**	.0082 (.0057)	1.44	-.0004 (.0008)	-.47	-.0029 (.0032)	-.92
Gender Match	-.0197 (.0110)	-1.79†	-.0061 (.0052)	-1.19	-.0004 (.0007)	-.52	-.0014 (.0029)	-.48
Country Match	.0050 (.0084)	.60	.0019 (.0039)	.49	.0007 (.0005)	1.39	.0024 (.0022)	1.10
Black Teacher	.0068 (.0169)	.40	.0113 (.0079)	1.43	-.0004 (.0010)	-.34	-.0025 (.0044)	-.56
Hispanic Teacher	-.0193 (.0181)	-1.06	-.0004 (.0085)	-.05	.0015 (.0011)	1.32	.0043 (.0047)	.91
Asian Teacher	-.0098 (.0247)	-.39	.0071 (.0116)	.61	-.0000 (.0015)	-.03	-.0009 (.0064)	-.14
Black Donor	-.0062 (.0169)	-.36	.0158 (.0079)	2.00*	.0001 (.0010)	.08	-.0010 (.0044)	-.24
Hispanic Donor	-.0028 (.0179)	-.16	-.0056 (.0084)	-.67	.0002 (.0011)	.19	-.0000 (.0047)	.00
Asian Donor	-.0015 (.0264)	-.06	.0121 (.0124)	.98	.0055 (.0016)	3.39**	.0256 (.0069)	3.71***
Ethnicity Match × Black	-.0064 (.0360)	-.18	-.0300 (.0168)	-1.78†	-.0011 (.0022)	-.48	-.0018 (.0094)	-.20
Ethnicity Match × Hispanic	.0157 (.0516)	.30	.0497 (.0242)	2.06*	-.0031 (.0032)	-.96	-.0098 (.0134)	-.73
Ethnicity Match × Asian	.2711 (.1221)	2.22*	.0019 (.0572)	.03	-.0067 (.0076)	-.88	-.0297 (.0318)	-.93

Unstandardized parameter estimates and (standard errors).
† = $p \leq .10$, * = $p < .05$, ** = $p < .01$, *** = $p < .001$

Web Appendix

Name Descriptive Information. The data contained 4693 unique surnames. The most common (Smith) occurred among donors 444 times. However, most names (4413; 94%) occurred fewer than 20 times among donors. Figure S1 graphs the commonness of surnames in the data. According to the data provided by Namsor, surnames originated in 105 countries. 55.9% of names were identified as British in origin. Next most common was Irish (11.6%) and Spanish (7.5%). The most common African country of origin was Liberia (2%). The most common Asian country of origin was India (0.5%).

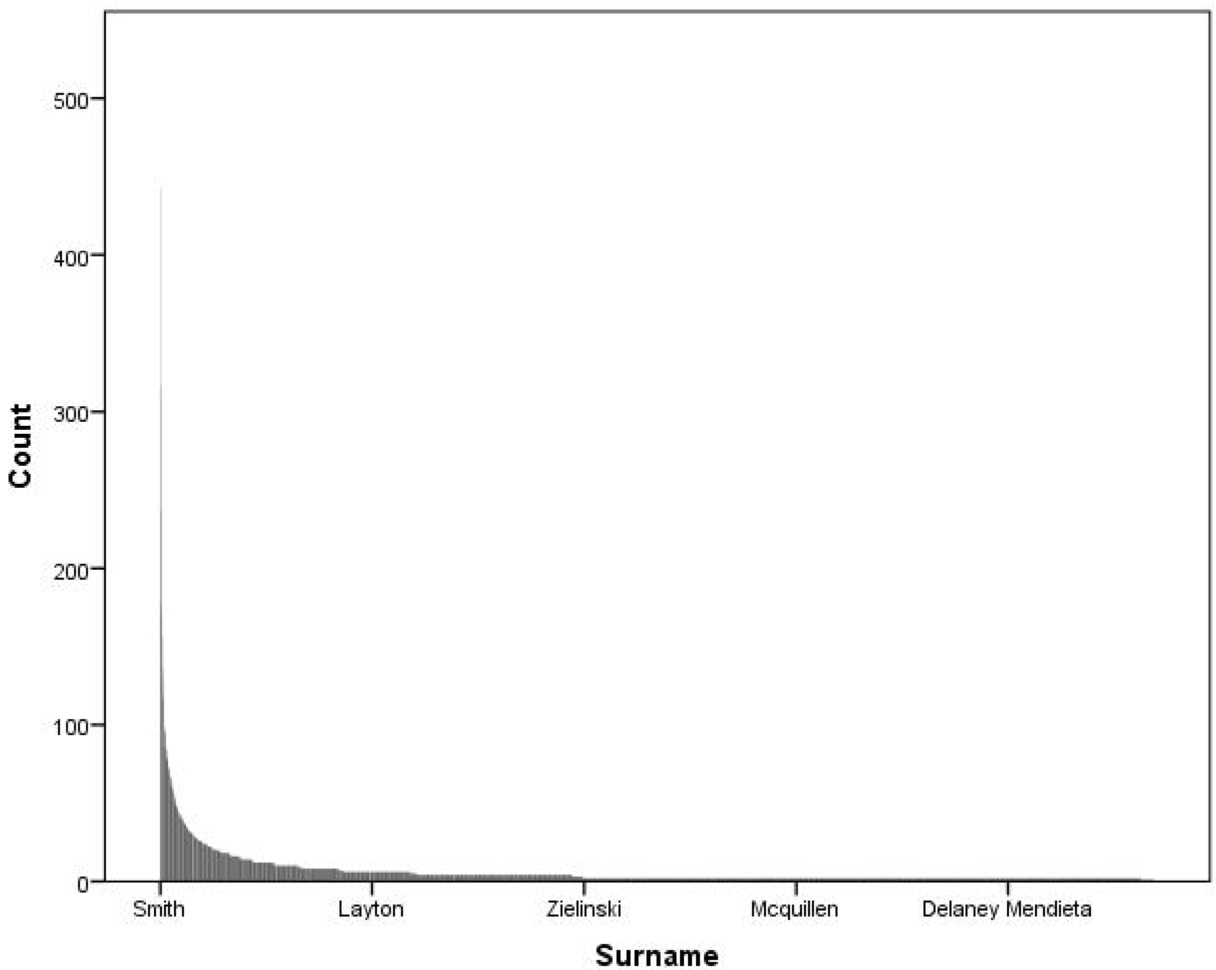

Figure S1 – Distribution of surname commonness in the data.

Census Data Analysis. In tables S1 through S4, we present OLS regression on each of our dependent variables: opened (yes/no), clicked (yes/no), donated (yes/no), donation amount (natural log transformation). However, in each of these tables, we use ethnicity information from the most likely ethnicity inferred from the surname only based on the 2000 US census. As in the main text, we present four model specifications with increasing granularity on ethnicity for each dependent variable. Gender data are as inferred using the machine learning approach, which takes both given and surnames into account.

Table S1 – OLS Regression on Opening Email (Census Data)

	Model 1		Model 2		Model 3		Model 4	
	Est (SE)	*t*-stat	Est (SE)	*t*-stat	Est (SE)	*t*-stat	Est (SE)	*t*-stat
Intercept	.259 (.010)	26.8***	.262 (.011)	24.1***	.260 (.011)	23.0***	.248 (.043)	5.73***
Name Match	.072 (.006)	12.3***	.072 (.006)	12.2***	.072 (.006)	12.1***	.072 (.006)	12.1***
Ethnicity Match (Census)	.009 (.009)	.94	.007 (.010)	.63	.007 (.011)	.69	.020 (.043)	.47
Female Donor	.025 (.009)	2.88**	.025 (.009)	2.85**	.025 (.009)	2.88**	.026 (.009)	2.90**
Gender Match	-.014 (.008)	-1.81†	-.014 (.008)	-1.75†	-.014 (.008)	-1.76†	-.014 (.008)	-1.80†
Black Teacher (Census)			-.017 (.023)	-.72	-.019 (.026)	-.74	.012 (.051)	.24
Hispanic Teacher (Census)			-.006 (.010)	-.55	-.005 (.011)	-.49	.009 (.044)	.21
Asian Teacher (Census)			.018 (.026)	.69	.006 (.029)	.22	-.016 (.049)	-.32
Black Donor (Census)					.006 (.026)	.25	.038 (.051)	.75
Hispanic Donor (Census)					.000 (.011)	.03	.015 (.044)	.35
Asian Donor (Census)					.028 (.032)	.88	-.007 (.056)	-.13
Ethnicity Match × Black							-.083 (.098)	-.85
Ethnicity Match × Hispanic							-.031 (.087)	-.36
Ethnicity Match × Asian							.098 (.100)	.99

† = $p < .10$, * = $p < .05$, ** = $p < .01$, *** = $p < .001$

Table S2 – OLS Regression on Clicking Link in Email (Census Data)

	Model 1		Model 2		Model 3		Model 4	
	Est (SE)	*t*-stat	Est (SE)	*t*-stat	Est (SE)	*t*-stat	Est (SE)	*t*-stat
Intercept	.040 (.005)	8.15***	.038 (.005)	6.91***	.037 (.006)	6.55***	.058 (.022)	2.66**
Name Match	.020 (.003)	6.95***	.020 (.003)	6.74***	.020 (.003)	6.65***	.020 (.003)	6.59***
Ethnicity Match (Census)	.009 (.005)	2.03*	.011 (.005)	2.15*	.012 (.005)	2.15*	-.009 (.022)	-.40
Female Donor	.001 (.004)	.32	.001 (.004)	.29	.001 (.004)	.32	.001 (.004)	.32
Gender Match	-.003 (.004)	-.78	-.003 (.004)	-.71	-.003 (.004)	-.72	-.003 (.004)	-.73
Black Teacher (Census)			-.001 (.012)	-.09	-.002 (.013)	-.17	-.023 (.026)	-.89
Hispanic Teacher (Census)			.002 (.005)	.46	.002 (.006)	.42	-.018 (.022)	-.82
Asian Teacher (Census)			.017 (.013)	1.28	.012 (.015)	.80	-.008 (.025)	-.31
Black Donor (Census)					.003 (.013)	.24	-.017 (.026)	-.67
Hispanic Donor (Census)					.000 (.006)	.07	-.020 (.022)	-.91
Asian Donor (Census)					.012 (.016)	.75	-.010 (.028)	-.35
Ethnicity Match × Black							.042 (.049)	.86
Ethnicity Match × Hispanic							.041 (.044)	.95
Ethnicity Match × Asian							.044 (.050)	-.88

†= $p < .10$, * = $p < .05$, ** = $p < .01$, *** = $p < .001$

Table S3 – OLS Regression on Donating (yes/no) (Census Data)

	Model 1		Model 2		Model 3		Model 4	
	Est (SE)	*t*-stat	Est (SE)	*t*-stat	Est (SE)	*t*-stat	Est (SE)	*t*-stat
Intercept	.0020 (.0008)	2.55*	.0023 (.0009)	2.68**	.0028 (.0009)	3.05**	.0014 (.0035)	.41
Name Match	.0012 (.0005)	2.52*	.0013 (.0005)	2.63**	.0013 (.0005)	2.81**	.0014 (.0005)	2.82**
Ethnicity Match (Census)	.0002 (.0008)	.26	-.0001 (.0008)	-.17	-.0006 (.0009)	-.65	.0008 (.0035)	.22
Female Donor	-.0017 (.0007)	-2.45*	-.0017 (.0007)	-2.44*	-.0017 (.0007)	-2.45*	-.0017 (.0007)	-2.45*
Gender Match	-.0000 (.0006)	-.04	-.0000 (.0006)	-.07	-.0000 (.0006)	-.06	-.0000 (.0006)	-.06
Black Teacher (Census)			-.0016 (.0019)	-.84	-.0012 (.0021)	-.56	-.0000 (.0042)	-.01
Hispanic Teacher (Census)			-.0004 (.0008)	-.45	.0002 (.0009)	.18	.0016 (.0036)	.45
Asian Teacher (Census)			-.0016 (.0021)	-.76	-.0011 (.0023)	-.48	-.0000 (.0040)	-.02
Black Donor (Census)					-.0012 (.0021)	-.58	-.0001 (.0041)	-.03
Hispanic Donor (Census)					-.0015 (.0009)	-1.59	-.0000 (.0035)	-.01
Asian Donor (Census)					-.0014 (.0025)	-.57	-.0004 (.0045)	-.08
Ethnicity Match × Black							-.0021 (.0079)	-.27
Ethnicity Match × Hispanic							-.0030 (.0070)	-.42
Ethnicity Match × Asian							-.0019 (.0080)	-.24

† = $p < .10$, * = $p < .05$, ** = $p < .01$, *** = $p < .001$

Table S4 – OLS Regression on Donation Amount (Natural Log Transformation) (Census Data)

	Model 1		Model 2		Model 3		Model 4	
	Est (SE)	*t*-stat	Est (SE)	*t*-stat	Est (SE)	*t*-stat	Est (SE)	*t*-stat
Intercept	.0084 (.0032)	2.62**	.0100 (.0036)	2.79**	.0118 (.0038)	3.13**	.0063 (.0144)	.44
Name Match	.0045(.0019)	2.33*	.0048 (.0020)	2.46*	.0052 (.0020)	2.63**	.0052 (.0020)	2.65**
Ethnicity Match (Census)	.0012 (.0031)	.37	-.0004 (.0035)	-.12	-.0021 (.0036)	-.58	.0033 (.0143)	.23
Female Donor	-.0081 (.0029)	-2.75**	-.0080 (.0029)	-2.75**	-.0081 (.0029)	-2.75**	-.0081 (.0029)	-2.75**
Gender Match	.0000 (.0027)	.03	.0000 (.0027)	.00	.0000 (.0027)	.01	.0000 (.0027)	.02
Black Teacher (Census)			-.0062 (.0076)	-.81	-.0047 (.0087)	-.54	.0000 (.0171)	.00
Hispanic Teacher (Census)			-.0021 (.0034)	-.60	.0000 (.0038)	.01	.0058 (.0147)	.39
Asian Teacher (Census)			-.0063 (.0085)	-.74	-.0044 (.0096)	-.46	-.0003 (.0164)	-.02
Black Donor (Census)					-.0048 (.0087)	-.56	-.0003 (.0169)	-.02
Hispanic Donor (Census)					-.0057 (.0037)	-1.52	.0000 (.0145)	.00
Asian Donor (Census)					-.0058 (.0105)	-.55	-.0015 (.0187)	-.08
Ethnicity Match × Black							-.0087 (.0324)	-.27
Ethnicity Match × Hispanic							-.0118 (.0289)	-.41
Ethnicity Match × Asian							-.0080 (.0331)	-.24

$^{\dagger} = p < .10$, * = $p < .05$, ** = $p < .01$, *** = $p < .001$

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%. Using the Census data, 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.

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 S5

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***	0.075***	0.084***	0.022***	0.022***	0.048***	0.001**	0.001**	0.002*	0.005**	0.005**	0.008*
	(0.005)	(0.005)	(0.011)	(0.003)	(0.003)	(0.006)	(0.000)	(0.000)	(0.001)	(0.002)	(0.002)	(0.004)
Natural-log of Name Frequency		-0.004	-0.002		-0.003***	0.002		0.000**	0.000		-0.002**	-0.001
		(0.002)	(0.003)		(0.001)	(0.001)		(0.000)	(0.000)		(0.001)	(0.001)
Condition X Natural-log of Name Frequency			-0.003			-0.009***			0.000			-0.001
			(0.004)			(.002)			(0.000)			(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***	0.075***	0.085***	0.022***	0.022***	0.049***	0.001**	0.001**	0.002*	0.005**	0.005**	0.008*
	(0.005)	(0.005)	(0.011)	(0.003)	(0.003)	(0.006)	(0.000)	(0.000)	(0.001)	(0.002)	(0.002)	(0.004)
Natural-log of Population Frequency (Census)		-0.003†	-0.001		-0.003***	0.001		0.000**	0.000		-0.002***	-0.001*
		(0.002)	(0.002)		(0.001)	(0.001)		(0.000)	(0.000)		(0.001)	(0.001)
Condition X Natural-log of Population Frequency (Census)			-0.003			-0.008***			0.000			-0.001
			(0.003)			(0.002)			(0.000)			(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 S6

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). † $p < .1$; * $p < .05$; ** $p < .01$; *** $p < .001$.