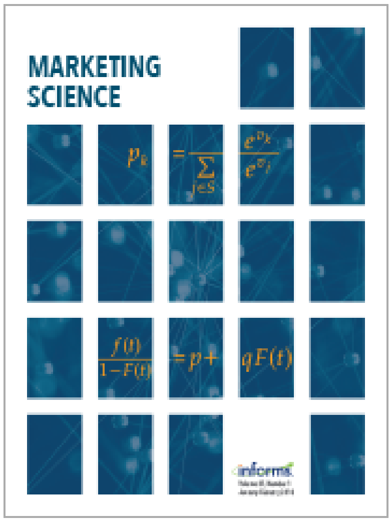


Marketing Science

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

Name Similarity Encourages Generosity: A Field Experiment in Email Personalization

Kurt P. Munz, Minah H. Jung, Adam L. Alter

To cite this article:
Kurt P. Munz, Minah H. Jung, Adam L. Alter (2020) Name Similarity Encourages Generosity: A Field Experiment in Email Personalization. Marketing Science 39(6):1071-1091. https://doi.org/10.1287/mksc.2019.1220

MARKETING SCIENCE
Vol. 39, No. 6, November–December 2020, pp. 1071–1091
ISSN 0732-2399 (print), ISSN 1526-548X (online)
http://pubsonline.informs.org/journal/mksc

Name Similarity Encourages Generosity: A Field Experiment in Email Personalization

Kurt P. Munz,[a,b] Minah H. Jung,[a] Adam L. Alter[a]

[a] Marketing Department, Leonard N. Stern School of Business, New York University, New York, New York 10012; [b] Marketing Department, Bocconi University, 20136 Milan, Italy

Contact: kurt.munz@stern.nyu.edu, https://orcid.org/0000-0002-5459-7602 (KPM); minah.jung@stern.nyu.edu, https://orcid.org/0000-0002-5748-3619 (MHJ); aalter@stern.nyu.edu, https://orcid.org/0000-0002-4698-8742 (ALA)

Received: September 28, 2017
Revised: July 31, 2018; May 15, 2019
Accepted: June 23, 2019
Published Online in Articles in Advance: April 10, 2020

https://doi.org/10.1287/mksc.2019.1220

Abstract. 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 measured 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 donate to teachers 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. 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 capture attention and bridge social distance.

History: This paper has been accepted for the *Marketing Science* Special Issue on Field Experiments.
Supplemental Material: Data files and the online appendix are available at https://doi.org/10.1287/mksc.2019.1220.

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

1. Introduction

During Coca-Cola's "Share a Coke" campaign, thousands of consumers opened emails to find an image of a Coke bottle displaying their name. The emails were part of a broader name-personalization marketing campaign that saw sales rise 2.5% at a time when category sales declined (Esterl 2014). The campaign fit with a growing trend in which marketers target consumers with increasing granularity (Ansari and Mela 2003, Khan et al. 2009). Today, 77% of U.S. marketers report personalizing email messages to target individual consumers (Evergage 2018).

There may be good reason for this trend. Recent evidence suggests that using a consumer's name in an email subject line can improve marketing-relevant outcomes (Sahni et al. 2018), and many consumers prefer brands and products that reflect their identities (Brendl et al. 2005, Summers et al. 2016). 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).

Yet a firm may not be universally well received when it uses a consumer's identity to attempt to persuade. Personalized communications may sometimes trigger concerns over privacy (Awad and Krishnan 2006, Wattal et al. 2012) or violate social norms if unknown brands come across as too familiar (Kim et al. 2019). More generally, aversive reactions may be particularly likely when consumers are more aware that their personal information is being used to persuade them (Goldfarb and Tucker 2011), making them feel like they are being manipulated (Friestad and Wright 1994). This could suggest that overt personalization in the context of a persuasive appeal may backfire with respect to marketers' aims.

In this paper, we focus on the context of charitable donations and ask if marketers can effectively use consumers' identities 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 increased donations. Specifically, we sent emails to potential donors to request they donate to support a particular teacher's classroom project. We randomized whether 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, and this pool was sufficiently large to facilitate genuine matching. A primary goal of this paper is to measure the effectiveness of various components of identity-based matching. To this end, we systematically varied whether a teacher and a potential donor shared a surname and measured other characteristics that can be inferred from the name, including gender, ethnicity, and the surname's country of origin. We also tested whether other measures of similarity, such as sharing only the initial letter of a surname, had a similar effect.

Past research has shown mixed effects of using names in marketing communications. Personalizing by name may be beneficial (e.g., Sahni et al. 2018), have no impact (e.g., Burger et al. 2004, Simonsohn 2011a), or work against marketing goals (e.g., Wattal et al. 2012). A priori, it was therefore difficult to predict whether matching an email recipient to a teacher in need along these identity-related dimensions would benefit the organization. Adding to the complexity, the effect of matching may vary by degree. For example, *subtle* matching (as in matching on dimensions that seem coincidental, such as ethnicity or name letters) may have a positive effect, but *overt* matching (as in full-name matching) may be less effective or even turn donors away. Although the design of our field experiment does not allow us to definitively answer the question of when positive versus negative outcomes may follow from name personalization, determining which of the opposing forces may dominate is an important managerial question. We suggest future research that may answer this question more directly in Section 6.

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 significantly positive effects for email open rates, clicks of the solicitation link in the email, donation likelihood, and average donations. These effects occurred above and beyond matching on ethnicity, gender, or national origin. Matching a person's name was effective in gaining a potential donor's attention, accounting for over 65% of the variance captured by the total model on open and click rates. The increased engagement with the email also led to more numerous and larger donations from the name-matched group. Conditional on clicking the link in the email, matching on ethnicity fostered greater generosity, whereas matching on name provided more modest additional benefit. Gender matching and mismatching also influenced generosity, though patterns differed depending on whether the donor and recipient were of similar ethnic background. Gender mismatches produced more generosity in general, but matched genders produced more generosity when the donor and recipient had ethnically matched names. We also found a small effect for initial-letter matching: people tend to be more generous toward randomly assigned 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.

This work contributes to the body of empirical work capitalizing on field experiments to study charitable giving (e.g., List 2011, Gneezy et al. 2014) and advertising (e.g., Eastlack and Rao 1989, Sahni 2015, Anderson et al. 2016, Sahni et al. 2017), and adds to a small but growing body of work seeking to bridge behavioral and quantitative marketing by testing behavioral theories in the field (e.g., Sudhir et al. 2016, Sahni et al. 2018).

In the next section, we first review the literature related to identity-related personalization in a marketing context, drawing competing hypotheses regarding the potential effect of a marketer using identity to persuade. In the third section, we elaborate on our contributions. In the fourth and fifth sections, we report our experimental procedure and empirical results. We conclude in the last section with a discussion of our findings in the context of the broader relevant literature and suggest an agenda for further exploration.

2. Background Literature

Personalization involves tailoring marketing communications using knowledge about an individual recipient. Personalization may mean selecting which products are offered to consumers to better fit their interests (Murthi and Sarkar 2003, Kramer et al. 2007, Arora et al. 2008, Zhang 2011) or selecting promotions on the basis of past transactions with a firm (Rossi et al. 1996, Anderson and Simester 2004, Zhang and Krishnamurthi 2004, Khan et al. 2009). In this section, we consider literature directly related to personalizing marketing communications using a consumer's name or elements of a consumer's identity inferable from the individual's name. The literature suggests that consumers can be attracted to or repelled by personalization, depending on how marketers deploy the tactic.

2.1. Identity Matching May Benefit the Firm

We discuss two main psychological processes that could drive positive consumer engagement with name-personalized marketing: attention and feelings of closeness to similar others.

2.1.1. Attention. One of the key roles of personalization is to attract attention (Ansari and Mela 2003). Ads can attract attention by being well aligned with consumers' interests (Rossi et al. 1996, Hauser et al. 2009, Urban et al. 2014), such as online ads based on recent browsing history (Lambrecht and Tucker 2013, Bleier and Eisenbeiss 2015), or by being intentionally attention grabbing, such as ads contained in pop-up windows (Goldfarb and Tucker 2011). Compared with financial incentives, a direct mail field experiment found a surprisingly large response to a financial services ad that included a photo of an attractive women, suggesting a role of attention independent of persuasiveness of actual information presented (Bertrand et al. 2010).

Names may be particularly attention grabbing, as people pay special attention to their own name (Cherry 1953). This seems to be a natural and automatic aspect of human nature, appearing early in child development (Newman 2005). 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. This form of egotism may be unconscious or implicit (Pelham et al. 2002, Jones et al. 2004, Pelham and Carvallo 2015), and can also lead people to prefer the initial letters of their own name to other letters of the alphabet (Nuttin 1985). These 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, with consumers preferring brands that match their initials (Brendl et al. 2005). Because people tend to automatically pay attention to things they like or value (Anderson et al. 2011, Motoki et al. 2018), and to self-relevant stimuli in general (Bargh 1982), attention may be one mechanism contributing to these outcomes (Jones et al. 2004).

2.1.2. Feelings of Closeness to Similar Others. Marketers personalize to foster a sense of similarity. This should benefit the firm, as people tend to like others who are similar to themselves (Byrne 1971). Social groups are also composed of similar individuals (e.g., Braun and Bonfrer 2011, Goel and Goldstein 2013), and there has been wide documentation of preferential treatment toward one's own group members (Tajfel and Turner 1979). For instance, we tend to donate more to charities that target the illnesses of our friends and loved ones (Small and Simonsohn 2008). Because our group members are similar to us, we may use similarity as a cue for treating others as though they were group members, and thus treating them more favorably. For example, in one correlational study, lenders on the microlending platform Kiva tended to make more loans to people of self-matching genders and professions (Galak et al. 2011). Emphasizing the similarities between a potential donor and recipient should induce a sense of closeness (Loewenstein and Small 2007), which should in turn prompt generosity.

Although sharing a name with someone may make the individual seem more self-similar, names can also serve as cues to explicit social groups. In a field experiment in India, Sudhir et al. (2016) found that fostering feelings of group identity using typical Christian or Hindu names had a significant effect on donations from members of matching religious groups. Names can also carry strong signals of group membership through shared ethnic or geographic origins. For example, someone with the surname Lundqvist is very likely to be Swedish or have Swedish ancestry.

Direct name matching (i.e., sharing a complete given name or surname with another person) may have additional benefits beyond signifying a social in-group. Because people only interact with others who share their names relatively rarely, some authors have suggested that a sense of serendipity or coincidence can drive helping behavior (Burger et al. 2004). For example, Burger et al. (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 with 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 that 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 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 may lead people to treat same-surname others more like family. However, this process may not explain the findings for given names (e.g., Burger et al. 2004).

2.2. Identity Matching May Not Be Effective

Although there are documented instances where personalizing marketing communications by name (Sahni et al. 2018) or social group (Sudhir et al. 2016) benefitted a firm, some studies have not found a link. For example, counter to expectations, in a field experiment in South Africa, when researchers manipulated whether a photographed person in an advertisement matched the ethnicity of a person receiving the ad, there was no significant effect (Bertrand et al. 2010). As mentioned earlier, others have documented benefits from sharing a name with someone only when it feels coincidental (Burger et al. 2004), suggesting a marketer may not be able to effectively use identity to persuade in a situation that doesn't seem serendipitous.

Moreover, findings that partial name matches (i.e., sharing initial name letters) can affect real-world decisions (Jones et al. 2004, Anseel and Duyck 2008) have been challenged on methodical grounds. Evidence for these effects has thus far relied on observations of secondary data, and some authors have questioned the causal role of name letters in affecting the outcomes (Simonsohn 2011a, b). If there is no causal relationship, personalizing marketing communications by name letters may be ineffective.

2.3. Identity Matching May Backfire

A marketer using elements of a person's identity to persuade can also lead to negative outcomes for a firm. Wattal et al. (2012) found that name-personalized email greetings led to lower response rates in their data, citing concerns about privacy. Using someone's identity to attempt to persuade may lead to reactance, or active countering against what a consumer perceives to be an attempt at manipulation (White et al. 2008). Negative reactions seem to be particularly likely when consumers do not feel in control of their personal data (Tucker 2014) or when they feel the data were collected in an unacceptable way (Kim et al. 2019). When marketing tactics are particularly overt or obtrusive (Goldfarb and Tucker 2011), consumers become more aware that marketers may be attempting to manipulate them (Friestad and Wright 1994, Campbell and Kirmani 2000). Thus, it seems that the likelihood of a negative reaction should increase as identity personalization becomes more overt and as perceived manipulation increases. Note, however, that whether a marketer action seems manipulative may depend on the nature of the existing relationship of the consumer with the firm (White et al. 2008, Wattal et al. 2012).

2.4. Identity Matching May Vary by Degree

The previous subsections described opposing forces that may result from personalizing marketing communications using a consumer's identity. We also discussed how some of these forces may interact. For example, it may be that identity matching grabs consumers' attention, but how they respond may depend on whether they feel manipulated (Goldfarb and Tucker 2011), their existing relationship with the firm (White et al. 2008, Wattal et al. 2012), or whether they feel the communication is appropriate (Kim et al. 2019).

The effect of identity matching may also vary by degree. That is, different levels of matching may have different effects. For example, consumers may perceive overt matching as manipulative, whereas subtle matching may be more effective. Consequently, subtle matching on dimensions such as ethnicity or name letters may have a positive effect because they seem coincidental, but comparatively overt matching, as with full names, may be less effective or counterproductive. Other nonlinear effects may also be possible if consumers exhibit diminishing sensitivity to greater degrees of matching, or if matching is ineffective below a certain threshold. This latter pattern may be possible if positive outcomes mostly result from increased attention, as consumers may not notice a match unless it is particularly conspicuous.

Even if matching leads to a positive effect, it may not be equally strong for everyone. For example, in the case of direct full-name matching, the effect may rely on a feeling of coincidence (Burger et al. 2004). When a name is uncommon, encountering another person with the same name should feel like a greater coincidence, and the effect should be enhanced compared to a match of a more common name. A similar prediction can be made if there is an effect of ego (Pelham et al. 2002). An identifier more uniquely associated with the self, such as an uncommon name or name letter, should lead to a greater ego response than one that could relate to many other people. Another example may be related to national origin. Rather than show preferential behavior toward their ethnic in-group per se (e.g., Caucasian), it is possible that people define their groups at the national level (e.g., Swedish).

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. Whereas marketing communications using consumers' personal data (such as their names) have garnered mixed results in the literature, an important managerial question remains as to which of the opposing forces dominates. We find that donors are more generous toward recipients who share their names. Explorations in the context of charity have come from secondary data (e.g., Chandler et al. 2008, Galak et al. 2011) or from smaller scale experiments (Oates and Wilson 2002, Burger et al. 2004, Guéguen et al. 2005). Our randomized field experiment provides evidence that marketers can use these principles to increase charitable giving at scale in actual markets. We discuss our findings in the context of the existing literature to propose future research to more directly test the boundary conditions for personalization. Furthermore, we quantify which aspects of similarity based on name (e.g. gender or ethnicity) are more and less effective. Marketers in other contexts may be able to use these insights when they cannot match match consumers to individual products by name.

We also contribute to understanding the underlying psychological mechanisms driving the effect of identity matching. Although insight into the psychological process is somewhat limited in a field experiment, our data suggest two mechanisms that may drive generosity toward similar others: attention and feelings of closeness to similar others. Importantly for marketing managers, these factors may affect different stages of the donation (or purchase) funnel. Using a person's name, or even the initial letters of the person's name, seems to attract attention. Increased attention can increase the number of people engaging with the organization by opening the email and clicking on the solicitation link, ultimately leading to more numerous donations (or purchases). Additionally, enhancing feelings of closeness by emphasizing similarity can provide additional benefit at the point of potential conversion.

Finally, we find randomized field experimental evidence for name-letter effects. Previously, these effects have been observed in natural settings only in secondary data (Pelham et al. 2002, Pelham and Carvallo 2015), but the causal effect of name letters has been questioned (Simonsohn 2011a, b). Skeptics pointed to alternative explanations, including selection issues, and confounding factors, including ethnicity. Although we did not set out to demonstrate these effects, because we observed name-letter effects in a field setting with randomization and controls for ethnicity, our results are among the strongest to support an effect of name letters on real-world outcomes to date.

4. Method

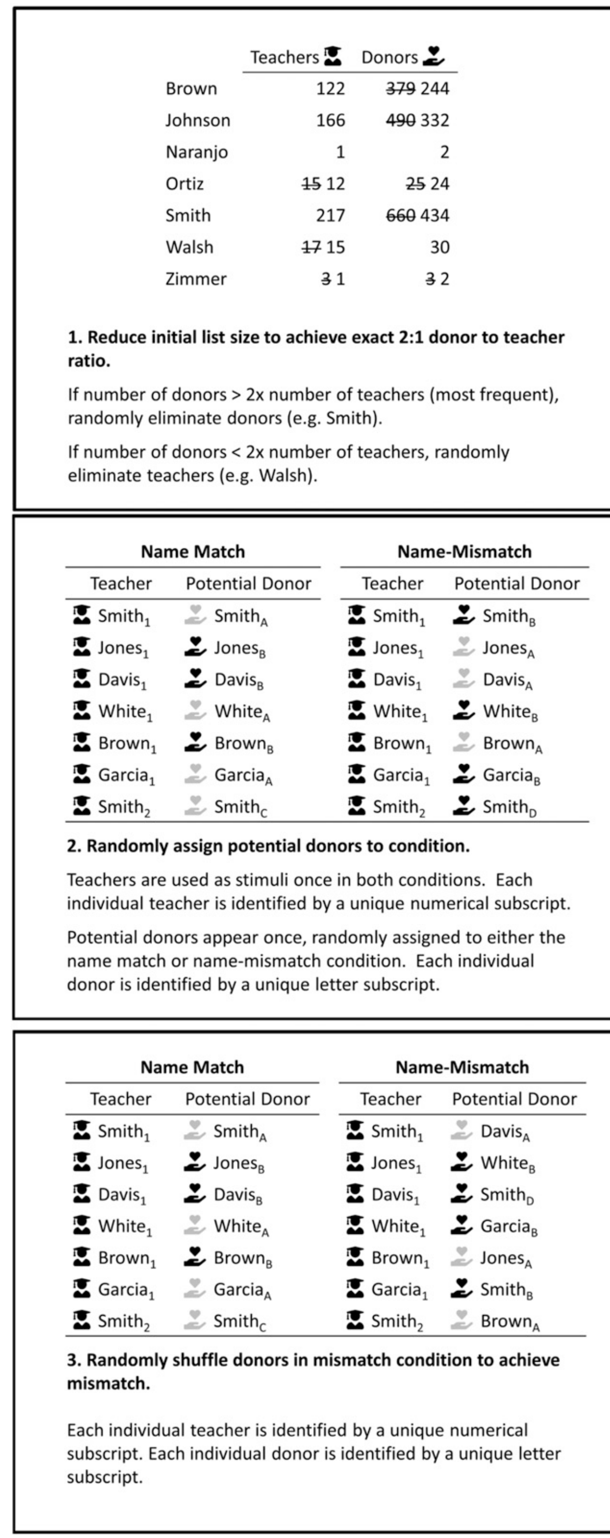
We report how we determined our sample size, all data exclusions, all manipulations, and all measures in the study (Simmons et al. 2012). We preregistered our plan for conducting this research prior to collecting any data and made it publicly available.[1]

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, and so on) of any one teacher project from having an outsized influence on our results. To ensure

Figure 1. Participants and Random Assignment



Note. Each panel depicts a step in determining how the size of the list was randomly reduced to achieve a 2:1 donor to teacher ratio and random assignment to condition.

that each teacher project appeared as a stimulus in both conditions exactly once, we randomly reduced the number of donors in most 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 A 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 B 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 the donor would read about. This is depicted in panel C 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 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.

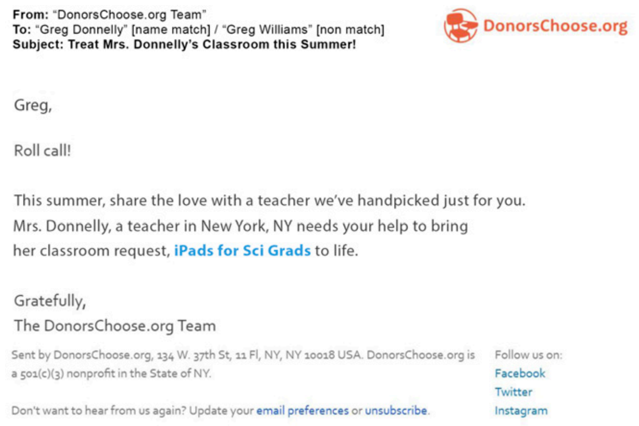
Our dependent measures were whether recipients opened the email (yes/no); whether recipients clicked on the link in the email (yes/no); whether recipients donated to support the project (yes/no); and how much the recipient donated.

5. Results

5.1. Name Matching

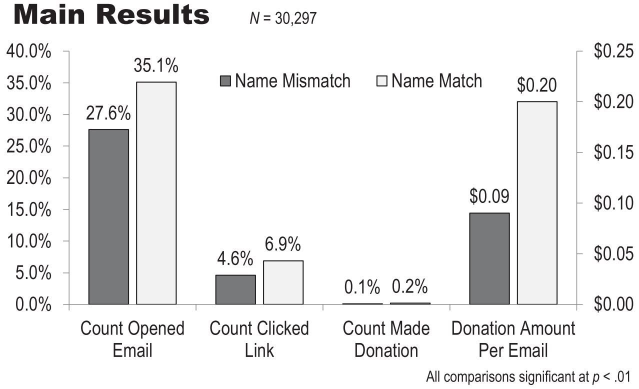
As depicted in Figure 3, we first we report the results of the name-matching manipulation without attempting to control for other variables. Name-matched email recipients were significantly more likely to open the email with the name-matched subject line, doing so 35.1% of the time compared with 27.6% of the time in the name-mismatch condition, $\chi^2(1, N = 30{,}297) = 197.3$, $p < 0.001$, $d = 0.162$. Similarly, name-matched email recipients were significantly more likely to click on the solicitation link in the email, doing so 6.9% of the time compared with 4.6% of the time in the name-mismatch condition, $\chi^2(1, N = 30{,}297) = 70.2$, $p < 0.001$, $d = 0.096$. Conditional on opening the initial email, the likelihood of clicking on the link was significantly greater in the name-match condition (19.6%) compared with the name-mismatch condition (16.8%), $\chi^2(1, N = 9{,}492) = 12.3$, $p < 0.001$, $d = 0.072$. Those in the name-match condition were significantly more likely to donate than those in the name-mismatch condition $\chi^2(1, N = 30{,}297) = 8.4$, $p = 0.004$, $d = 0.033$. Of the 43 donations, 31 (72.1%) were made by those in the name-match condition. Conditional on clicking on the link, those in the name-match condition donated

Figure 2. (Color online) Email Sent to Potential Donors



Notes. 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.

Figure 3. Effects of Randomly Assigned Name-Match Condition



Note. Name-matched participants responded positively to the treatment.

at a higher rate (3.0%) compared with the name-mismatch condition (1.7%), but the effect was significant only with 90% confidence, $\chi^2(1, N = 1{,}740) = 2.8$, $p = 0.095$, $d = 0.080$.

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 value, which revealed the amount donated to be higher in the name-match group $Z = 2.90$, $p = 0.004$. A significant result was also obtained by calculating an analysis of variance on a variable computed by adding one and natural log-transforming the donation amount $F(1, 30295) = 8.02$, $p = 0.005$, $d = 0.016$.

Conditional on making a donation, there was no significant difference in donation amount between the conditions. That is, the average amount donated (among those who donated) was about the same in both groups. However, as depicted in Figure 4, this analysis may be misleading because our manipulation induced people to donate who otherwise would not have, and these people are not likely to give a large amount. We wondered if there may also be an effect of donation size when looking at a more appropriate comparison set. Specifically, we wished to compare across an equal number of donors from each condition. To answer this question, we followed a procedure reported by Sudhir et al. (2016). Specifically, within each condition we assigned a rank to each donation in descending order based on size and conducted a matched pair analysis with the pairs matched on rank. That is, this analysis compares the top donors, looking only at an equal number of donors from each condition. Because there were 12 donations in the name-mismatch condition, this means comparing the top 12 donors across both conditions. This analysis revealed a significant difference in donation amount $t(11) = 4.28$, $p = 0.001$.

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 ethnicity, gender, or national origin. We discuss initial surname letters in Section 5.3. 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 characteristics. Can a marketer achieve similar results to name matching by matching on ethnic origin, for example?

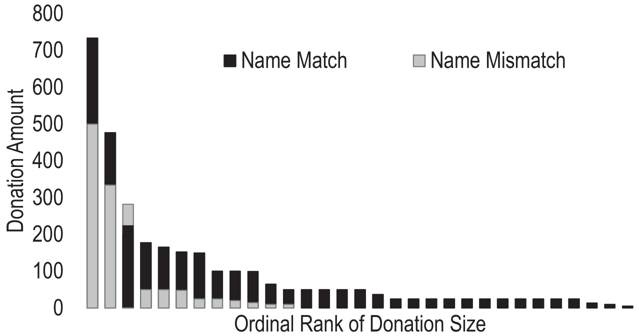
We attempted this analysis using two methods. First, we partnered with a third-party company that classified gender, ethnicity, and national origins of names using a machine learning algorithm trained on large data sets. Second, we appended U.S. Census data for each surname regarding the most likely 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 its algorithm using data sets from across the world, and claims accuracy of about 75% for ethnicity in the United States 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 United States 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, whereas Karen Petrossian is more likely to be a male Armenian name.

Using this approach, 18,488 (61.0%) of the donors' names were classified as white, 6,820 (22.5%) black,

Figure 4. Donations by Condition Ordered by Donation Size



Notes. The name-match group yielded a greater number of donations, and the donations were larger when comparing an equal number of donations from both conditions matched on rank of the donation (largest, second largest, etc.). The paired analysis compares only those ranks applicable to both groups (does not include zeros).

Table 1. Binary Logistic Regression on Opening the Email

Variable name	1	2	3	4	5	6
Matching						
Name match	0.327		0.337	0.326	0.332	0.283
	(0.028)***		(0.027)***	(0.028)***	(0.027)***	(0.042)***
Ethnicity match	0.045	0.128		0.044	0.047	−0.081
	(0.030)	(0.029)***		(0.030)	(0.030)	(0.066)
Gender match	−0.057	−0.055	−0.055		−0.057	−0.120
	(0.047)	(0.047)	(0.047)		(0.047)	(0.057)*
Country match	0.019	0.110	0.022	0.019		0.020
	(0.027)	(0.026)***	(0.027)	(0.027)		(0.027)
Degrees of matching						
Ethnicity and name						0.096
						(0.078)
Ethnicity and gender						0.129
						(0.075)†
Ethnicity, name, and gender						−0.030
						(0.077)
Control variables						
Female teacher	−0.015	−0.024	−0.013	−0.049	−0.015	−0.010
	(0.046)	(0.046)	(0.046)	(0.037)	(0.046)	(0.046)
Black teacher	0.000	0.020	−0.014	0.000	0.001	−0.001
	(0.033)	(0.033)	(0.032)	(0.033)	(0.033)	(0.033)
Hispanic teacher	−0.079	−0.059	−0.086	−0.081	−0.080	−0.086
	(0.050)	(0.049)	(0.050)†	(0.050)	(0.050)	(0.050)†
Asian teacher	0.076	0.099	0.059	0.077	0.075	0.070
	(0.080)	(0.079)	(0.079)	(0.080)	(0.080)	(0.080)
Female donor	0.112	0.102	0.110	0.070	0.113	0.111
	(0.047)*	(0.046)*	(0.047)*	(0.031)*	(0.047)*	(0.047)*
Black donor	0.003	0.023	−0.011	0.003	0.005	0.004
	(0.033)	(0.033)	(0.31)	(0.033)	(0.033)	(0.033)
Hispanic donor	0.017	0.035	0.010	0.017	0.016	0.009
	(0.049)	(0.049)	(0.49)	(0.049)	(0.049)	(0.050)
Asian donor	0.077	0.126	0.058	0.077	0.076	0.077
	(0.081)	(0.080)	(0.080)	(0.081)	(0.081)	(0.081)
Constant	−1.025	−0.950	−0.999	−1.002	−1.021	−0.969
	(0.053)***	(0.052)***	(0.050)***	(0.049)***	(0.052)***	(0.058)***
N	28,737	28,737	28,737	28,737	28,737	28,737
−2 log likelihood	35,512.455	35,561.953	35,514.787	35,513.936	35,512.995	35,506.703
Cox and Snell (1989)R^2	0.006796	0.001963	0.006716	0.006745	0.006779	0.006995

Note. Unstandardized parameter estimates and (standard errors).
†$p < 0.10$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

2,888 (9.5%) Hispanic, 972 (3.2%) Asian, and 1,129 (3.7%) were not classified.[3] The distribution of ethnicities for teachers' names was about the same, as intended by our experimental design.

For gender, 22,242 (73.4%) of the donors' names were classified as female, 6,494 (21.4%) as male, 1,082 (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 online appendix for additional descriptive details.

With these additional data about ethnicity, gender, and country appended to our original data set, we conducted binary logistic regressions on each of our dependent measures (ordinary least squares (OLS) regression on donation amount). The results are reported in Tables 1–7. We used these regressions to help us answer three primary questions. First, does the effect of name matching hold when controlling

Table 2. Binary Logistic Regression on Clicking the Link in the Email

Variable name	1	2	3	4	5	6
Matching						
Name match	0.397		0.416	0.397	0.399	0.373
	(0.056)***		(0.054)***	(0.056)***	(0.054)***	(0.085)***
Ethnicity match	0.088	0.186		0.086	0.088	–0.040
	(0.059)	(0.058)**		(0.059)	(0.059)	(0.139)
Gender match	–0.121	–0.119	–0.117		–0.121	–0.185
	(0.098)	(0.098)	(0.098)		(0.098)	(0.119)
Country match	0.006	0.115	0.012	0.005		0.007
	(0.054)	(0.052)*	(0.054)	(0.054)		(0.054)
Degrees of matching						
Ethnicity and name						0.088
						(0.157)
Ethnicity and gender						0.153
						(0.156)
Ethnicity, name, and gender						–0.065
						(0.156)
Control variables						
Female teacher	0.101	0.090	0.105	0.029	0.101	0.107
	(0.096)	(0.096)	(0.096)	(0.074)	(0.096)	(0.096)
Black teacher	–0.063	–0.042	–0.085	–0.064	–0.063	–0.064
	(0.066)	(0.066)	(0.064)	(0.066)	(0.066)	(0.066)
Hispanic teacher	–0.062	–0.041	–0.071	–0.064	–0.062	–0.065
	(0.104)	(0.102)	(0.103)	(0.104)	(0.104)	(0.105)
Asian teacher	0.103	0.130	0.077	0.105	0.103	0.099
	(0.154)	(0.153)	(0.152)	(0.154)	(0.154)	(0.154)
Female donor	0.077	0.065	0.073	–0.015	0.077	0.075
	(0.097)	(0.097)	(0.097)	(0.061)	(0.097)	(0.097)
Black donor	0.101	0.125	0.073	0.101	0.102	0.103
	(0.065)	(0.065)†	(0.062)	(0.065)	(0.065)	(0.065)
Hispanic donor	–0.019	–0.004	–0.031	–0.019	–0.019	–0.023
	(0.104)	(0.102)	(0.103)	(0.104)	(0.104)	(0.105)
Asian donor	0.279	0.339	0.244	0.280	0.279	0.280
	(0.148)†	(0.148)*	(0.146)†	(0.148)†	(0.148)†	(0.148)†
Constant	–3.154	–3.050	–3.103	–3.102	–3.152	–3.104
	(0.109)***	(0.107)***	(0.103)***	(0.098)***	(0.108)***	(0.120)***
N	28,737	28,737	28,737	28,737	28,737	28,737
–2 log likelihood	12,504.282	12,555.416	12,506.470	12,505.856	12,504.295	12,503.051
Cox and Snell R^2	0.002716	0.000939	0.002640	0.002661	0.002715	0.002758

Note. Unstandardized parameter estimates and (standard errors).
$^{\dagger}p < 0.10$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

for important variables? Second, what proportion of the variance in our data are explained by each component of matching: name, ethnicity, gender, and country? Third, does the degree of matching affect generosity?

5.2.1.1. Effect of Name Matching, Controlling for Other Factors. Model 1 in each regression reported in Tables 1–7 helps to answer the first question regarding the robustness of the name-match manipulation when controlling for other variables. In this model, we included binary variables indicating whether a potential donor and teacher match on surname, ethnicity, gender, and country of origin of the surname (e.g., Irish, Russian), as well as dummy variables capturing ethnicity and gender of both the teacher and the donor. We observed that the effect of being randomly assigned to the name-match condition was associated with more favorable outcomes for opening the email (Table 1), clicking on the link in the email (Table 2), clicking on the link conditional on first opening the email (Table 3), donating (Table 4), and donation amount (Table 6). These effects occurred above and beyond the effects of matching on ethnicity, gender, and country of origin. Name matching does not appear to have a significant effect on donation behavior, conditional on clicking on the link in the email (Tables 5 and 7), suggesting that the causal mechanism may occur earlier in the donation funnel, rather than once a potential donor has already clicked on the link.

Table 3. Binary Logistic Regression on Clicking the Link in the Email, Conditional on First Opening the Email

Variable name	1	2	3	4	5	6
Matching						
Name match	0.181		0.195	0.181	0.178	0.183
	(0.060)**		(0.058)***	(0.060)**	(0.058)**	(0.091)*
Ethnicity match	0.061	0.107		0.059	0.060	0.019
	(0.064)	(0.062)†		(0.064)	(0.064)	(0.149)
Gender match	–0.095	–0.094	–0.092		–0.095	–0.113
	(0.105)	(0.105)	(0.105)		(0.105)	(0.127)
Country match	–0.009	0.040	–0.005	–0.010		–0.009
	(0.058)	(0.056)	(0.058)	(0.058)		(0.058)
Degrees of matching						
Ethnicity and name						0.030
						(0.169)
Ethnicity and gender						0.064
						(0.168)
Ethnicity, name, and gender						–0.048
						(0.167)
Control variables						
Female teacher	0.130	0.125	0.133	0.072	0.129	0.131
	(0.102)	(0.102)	(0.102)	(0.079)	(0.102)	(0.103)
Black teacher	–0.068	–0.060	–0.083	–0.068	–0.068	–0.067
	(0.071)	(0.071)	(0.069)	(0.071)	(0.070)	(0.071)
Hispanic teacher	–0.004	0.004	–0.009	–0.005	–0.003	–0.003
	(0.113)	(0.112)	(0.112)	(0.113)	(0.113)	(0.113)
Asian teacher	0.043	0.055	0.026	0.045	0.043	0.043
	(0.167)	(0.167)	(0.165)	(0.167)	(0.167)	(0.167)
Female donor	–0.002	–0.010	–0.004	–0.075	–0.003	–0.003
	(0.104)	(0.103)	(0.104)	(0.065)	(0.104)	(0.104)
Black donor	0.112	0.124	0.092	0.112	0.111	0.112
	(0.070)	(0.070)†	(0.067)	(0.070)	(0.070)	(0.070)
Hispanic donor	–0.036	–0.028	–0.044	–0.035	–0.036	–0.035
	(0.112)	(0.111)	(0.111)	(0.112)	(0.112)	(0.113)
Asian donor	0.262	0.286	0.239	0.261	0.261	0.262
	(0.163)	(0.162)†	(0.160)	(0.163)	(0.163)	(0.163)
Constant	–1.696	–1.643	–1.662	–1.654	–1.698	–1.686
	(0.116)***	(0.114)***	(0.110)***	(0.105)***	(0.115)***	(0.127)***
N	8,988	8,988	8,988	8,988	8,988	8,988
–2 log likelihood	8,521.385	8,530.487	8,522.292	8,522.225	8,521.408	8,521.239
Cox and Snell R^2	0.002469	0.001458	0.002368	0.002376	0.002466	0.002485

Note. Unstandardized parameter estimates and (standard errors).
†$p < 0.10$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

5.2.1.2. Variance Decomposition. What proportion of the variance in our data are explained by each component of matching? To decompose the variance, we ran a series of regressions (Models 2–5 in Tables 1–7), omitting one of the components of matching (name, ethnicity, gender, country) from each model in succession. Comparing the R^2 from the base model (Model 1) to the model with a match variable omitted enabled us to understand the proportion of base model variance accounted for by each variable alone.

For opening the email (Table 1), name matching was far and away most influential. Of the variance explained by the full model (Model 1), 71.1% of it can be explained by the name-match variable alone. This compares to ethnicity matching (1.2%), gender matching (0.8%), and country matching (0.3%). The remaining variance was accounted for by our con-trol variables.

For clicking on the link (Table 2), we observed a similar pattern. Name matching accounted for 65.4% of the variance, with matching on ethnicity (2.8%), gender (2.0%), and country (< 0.1%) accounting for substantially less of the overall R^2. Conditional on having already opened the email (Table 3), name matching explained 40.9% of the variance in clicking on the link, compared with 4.1% for ethnicity matching, 3.8% for gender matching, and 0.1% for country matching.

Examining donation incidence (Table 4), we found an interesting pattern. As before, overall we saw that

Table 4. Binary Logistic Regression on Donating (Yes/No)

Variable name	1	2	3	4	5	6
Matching						
Name match	0.920		1.001	0.920	0.882	0.659
	(0.377)*		(0.375)**	(0.377)*	(0.366)*	(0.753)
Ethnicity match	0.937	1.123		0.933	0.934	−0.306
	(0.589)	(0.583)†		(0.589)	(0.590)	(0.998)
Gender match	−0.092	−0.082	−0.053		−0.097	−2.043
	(0.505)	(0.504)	(0.510)		(0.505)	(1.146)†
Country match	−0.139	0.084	−0.131	−0.141		−0.144
	(0.331)	(0.322)	(0.331)	(0.331)		(0.332)
Degrees of matching						
Ethnicity and name						0.673
						(1.076)
Ethnicity and gender						2.717
						(1.360)*
Ethnicity, name, and gender						−0.490
						(0.932)
Control variables						
Female teacher	0.069	0.044	0.133	0.054	0.065	0.126
	(0.490)	(0.490)	(0.490)	(0.480)	(0.490)	(0.492)
Black teacher	−1.054	−1.025	−1.260	−1.055	−1.058	−1.082
	(0.662)	(0.665)	(0.607)*	(0.662)	(0.662)	(0.672)
Hispanic teacher	0.711	0.555	0.159	0.708	0.737	0.685
	(0.813)	(0.787)	(0.678)	(0.813)	(0.813)	(0.838)
Asian teacher	−15.200	−15.160	−15.039	−15.196	−15.210	−15.139
	(1,260.13)	(1,272.53)	(1,345.41)	(1,260.14)	(1,257.34)	(1,250.10)
Female donor	−0.925	−0.954	−0.953	−0.996	−0.928	−0.922
	(0.503)†	(0.502)†	(0.508)†	(0.319)**	(0.503)†	(0.507)†
Black donor	−0.069	−0.014	−0.610	−0.070	−0.075	−0.002
	(0.070)	(0.618)	(0.486)	(0.617)	(0.617)	(0.620)
Hispanic donor	−2.161	−1.852	−1.779	−2.160	−2.195	−2.157
	(1.251)†	(1.204)	(1.119)	(1.250)†	(1.253)†	(1.257)†
Asian donor	1.332	1.472	0.578	1.332	1.337	1.303
	(0.880)	(0.881)†	(0.734)	(0.881)	(0.880)	(0.880)
Constant	−6.939	−6.593	−6.195	−6.931	−6.973	−6.297
	(0.753)***	(0.728)***	(0.569)***	(0.749)***	(0.749)***	(0.811)***
N	28,737	28,737	28,737	28,737	28,737	28,737
−2 log likelihood	568.918	575.478	571.683	568.951	569.095	562.331
Cox and Snell R^2	0.001293	0.001065	0.001197	0.001292	0.001287	0.001522

Note. Unstandardized parameter estimates and (standard errors).
$^{\dagger}p < 0.10$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

name matching was the most effective, accounting for 17.6% of the variance captured by Model 1, considerably more than the percentage explained by matching on ethnicity (7.4%), country (0.5%), or gender (0.1%). However, conditional on having already clicked on the link in the email (Table 5), the likelihood of donating was most influenced by matching on ethnicity, accounting for 8.6% of the variance of the total model. Name matching accounted for 5.5%, country matching for 0.4%, and gender matching for 0.1%. This may suggest that later in the donation funnel, matching on ethnicity may facilitate greater generosity, whereas name matching is much more effective in capturing attention.

The pattern was the same for donation amount (Table 6). Name matching captured the highest percentage (14.6%) of the variance, with ethnicity (4.2%), country (2.0%), and gender (< 0.1%) capturing less. However, conditional on clicking on the link (Table 7), the variance in donation amounts was explained to a greater extent by ethnicity (6.0%) than name matching (3.9%), country matching (1.9%), or gender matching (0.1%).

These models also confirm some intuitions. Across all models tested, removing ethnicity matching from the model (Model 3), made the apparent effect of name matching larger (compared with Model 1). This suggests that the effect of name matching is at least

Table 5. Binary Logistic Regression on Donating (Yes/No), Conditional on First Clicking the Link in the Email

Variable name	1	2	3	4	5	6
Matching						
Name match	0.447		0.556	0.477	0.448	0.178
	(0.384)		(0.382)	(0.384)	(0.376)	(0.784)
Ethnicity match	0.920	1.014		0.917	0.914	−0.232
	(0.596)	(0.592)†		(0.596)	(0.596)	(1.012)
Gender match	−0.068	−0.070	−0.030		−0.087	−1.986
	(0.517)	(0.517)	(0.519)		(0.514)	(1.159)†
Country match	−0.122	−0.026	−0.104	−0.126		−0.137
	(0.338)	(0.331)	(0.338)	(0.336)		(0.338)
Degrees of matching						
Ethnicity and name						0.617
						(1.106)
Ethnicity and gender						2.537
						(1.374)†
Ethnicity, name, and gender						−0.327
						(0.949)
Control variables						
Female teacher	0.033	0.042	0.060	0.020	0.040	0.107
	(0.501)	(0.501)	(0.501)	(0.489)	(0.500)	(0.507)
Black teacher	−0.950	−0.966	−1.188	−0.949	−0.956	−1.059
	(0.657)	(0.657)	(0.611)†	(0.657)	(0.656)	(0.668)
Hispanic teacher	0.848	0.716	0.350	0.847	0.877	0.709
	(0.842)	(0.823)	(0.720)	(0.841)	(0.841)	(0.891)
Asian teacher	−18.201	−18.203	−17.942	−18.193	−18.206	−18.186
	(5,061.71)	(5,074.17)	(5,374.78)	(5,062.32)	(5,058.66)	(5,015.55)
Female donor	−0.904	−0.935	−0.905	−0.956	−0.892	−0.887
	(0.515)†	(0.515)†	(0.517)†	(0.328)**	(0.513)†	(0.521)†
Black donor	−0.106	−0.075	−0.653	−0.106	−0.116	0.016
	(0.620)	(0.621)	(0.491)	(0.620)	(0.619)	(0.631)
Hispanic donor	−2.150	−1.961	−1.775	−2.149	−2.184	−2.061
	(1.283)†	(1.256)	(1.159)	(1.283)†	(1.284)†	(1.306)
Asian donor	1.075	1.157	0.359	1.075	1.062	1.159
	(0.906)	(0.904)	(0.762)	(0.906)	(0.906)	(0.930)
Constant	−3.807	−3.596	−3.062	−3.798	−3.846	−3.187
	(0.774)***	(0.749)***	(0.588)***	(0.770)***	(0.768)***	(0.824)***
N	1,641	1,641	1,641	1,641	1,641	1,641
−2 log likelihood	346.655	348.284	349.199	346.672	346.784	340.773
Cox and Snell R^2	0.017814	0.016839	0.016290	0.017804	0.017737	0.021328

Note. Unstandardized parameter estimates and (standard errors).
$^{\dagger}p < 0.10$; $^{**}p < 0.01$; $^{***}p < 0.001$.

partially driven by favoritism toward one's own ethnic in-group. Indeed, we also found that when removing the name-match variable (Model 2), the variance is captured mostly by ethnicity and country matching.

5.2.1.3. Degree of Matching. Does degree of matching affect generosity? We approached this question by testing if additional components of matching improve or detract from marketers' outcomes. For example, does matching on both name and ethnicity affect generosity? Does the effect change if the match is too close, such as matching on name, ethnicity, and gender? Model 6 in Tables 1–7 reports the results of regressions including these "degree of match" variables. In general, the pattern of coefficients suggested that matching along two dimensions benefits the firm more than matching on only one. Matching on ethnicity and surname or ethnicity and gender revealed positive coefficients for each dependent variable, above and beyond matching on each aspect independently, though inconsistent with respect to statistical significance. In contrast, the direction of the effect was reversed for matching on surname, gender, and ethnicity. Note, however, that this reversal never reached the threshold for significance, and thus should be more conservatory interpreted as having no additional benefit. In sum, the regressions weakly supported the conclusion that overall closer similarity between a potential donor and a teacher in need increased charitable behavior, though only to a point.

Table 6. OLS Regression on the Natural Log Transformed Donation Amount

Variable name	1	2	3	4	5	6
Matching						
Name match	0.005		0.005	0.005	0.004	0.001
	(0.002)*		(0.002)**	(0.002)*	(0.002)*	(0.003)
Ethnicity match	0.003	0.004		0.003	0.002	–0.004
	(0.002)	(0.002)†		(0.002)	(0.002)	(0.005)
Gender match	0.000	0.000	0.000		0.000	–0.002
	(0.003)	(0.003)	(0.003)		(0.003)	(0.004)
Country match	–0.002	0.000	–0.001	–0.002		–0.002
	(0.002)	(0.002)	(0.002)	(0.002)		(0.002)
Degrees of matching						
Ethnicity and name						0.009
						(0.005)†
Ethnicity and gender						0.006
						(0.005)
Ethnicity, name, and gender						–0.004
						(0.005)
Control variables						
Female teacher	0.000	0.000	0.000	0.000	0.000	0.000
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Black teacher	–0.005	–0.004	–0.005	–0.005	–0.005	–0.005
	(0.002)†	(0.002)†	(0.002)*	(0.002)†	(0.002)*	(0.002)*
Hispanic teacher	–0.002	–0.001	–0.002	–0.002	–0.001	–0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Asian teacher	–0.008	–0.007	–0.009	–0.008	–0.008	–0.008
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Female donor	–0.008	–0.008	–0.008	–0.008	–0.008	–0.008
	(0.003)*	(0.003)*	(0.003)*	(0.006)***	(0.003)*	(0.003)*
Black donor	–0.002	–0.002	–0.003	–0.002	–0.002	–0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Hispanic donor	–0.005	–0.005	–0.005	–0.005	–0.005	–0.006
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Asian donor	0.007	0.008	0.006	0.007	0.007	0.007
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Constant	0.011	0.012	0.012	0.011	0.010	0.013
	(0.004)**	(0.004)**	(0.003)***	(0.003)**	(0.004)**	(0.004)**
N	28,736	28,736	28,736	28,736	28,736	28,736
R^2	0.001291	0.001103	0.001237	0.001291	0.001265	0.001418

Note. Unstandardized parameter estimates and (standard errors).
†$p < 0.10$; *$p < 0.0$; **$p < 0.01$; ***$p < 0.001$.

Interestingly, opposing forces may be at play when it comes to gender. When matched on gender and ethnicity, the effect appears to be positive, consistent with past research showing generosity toward similar others (Galak et al. 2011). However, there also seems to be an opposing effect such that people are more generous toward people of the opposite gender. As reported in the online appendix, we tested for interactive effects (i.e., do male potential donors respond differently from females to gender-matched teachers?), but the interactions did not reach significance on any of the variables we tested.

An unexpected finding involved donor gender effects. Female donors were significantly more likely to open the email, whereas male donors were more likely to donate, and donated significantly more.

5.2.2. Census Approach. We also turned to data from the 2000 U.S. 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.

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

Table 7. OLS Regression on the Natural Log Transformed Donation Amount, Conditional on Clicking the Email Link

Variable name	1	2	3	4	5	6
Matching						
Name match	0.037		0.048	0.037	0.030	−0.002
	(0.034)		(0.033)	(0.034)	(0.033)	(0.052)
Ethnicity match	0.050	0.059		0.050	0.048	−0.040
	(0.037)	(0.036)†		(0.037)	(0.037)	(0.085)
Gender match	0.013	0.013	0.016		0.009	−0.024
	(0.061)	(0.061)	(0.061)		(0.061)	(0.074)
Country match	−0.025	−0.016	−0.022	−0.024		−0.024
	(0.033)	(0.032)	(0.033)	(0.033)		(0.033)
Degrees of matching						
Ethnicity and name						0.089
						(0.096)
Ethnicity and gender						0.077
						(0.096)
Ethnicity, name, and gender						−0.030
						(0.096)
Control variables						
Female teacher	−0.015	−0.015	−0.016	−0.008	−0.014	−0.010
	(0.059)	(0.059)	(0.003)	(0.045)	(0.059)	(0.059)
Black teacher	−0.072	−0.071	−0.085	−0.072	−0.074	−0.074
	(0.040)†	(0.040)†	(0.039)*	(0.040)†	(0.040)*	(0.040)†
Hispanic teacher	−0.002	−0.003	−0.004	−0.002	−0.001	−0.012
	(0.067)	(0.067)	(0.067)	(0.067)	(0.067)	(0.068)
Asian teacher	−0.134	−0.132	−0.148	−0.135	−0.134	−0.138
	(0.094)	(0.094)	(0.093)	(0.094)	(0.094)	(0.094)
Female donor	−0.137	−0.139	−0.138	−0.127	−0.135	−0.134
	(0.060)*	(0.060)*	(0.060)*	(0.037)***	(0.060)*	(0.060)*
Black donor	−0.033	−0.031	−0.051	−0.033	−0.036	−0.032
	(0.040)	(0.040)	(0.038)	(0.040)	(0.040)	(0.040)
Hispanic donor	−0.088	−0.084	−0.095	−0.088	−0.088	−0.089
	(0.068)	(0.068)	(0.068)	(0.068)	(0.068)	(0.068)
Asian donor	0.078	0.084	0.058	0.079	0.077	0.081
	(0.091)	(0.091)	(0.090)	(0.091)	(0.091)	(0.091)
Constant	0.200	0.212	0.230	0.194	0.193	0.236
	(0.068)**	(0.067)**	(0.064)***	(0.061)**	(0.067)**	(0.074)**
N	1,640	1,640	1,640	1,640	1,640	1,640
R^2	0.018044	0.017341	0.016953	0.018018	0.017693	0.019074

Note. Unstandardized parameter estimates and (standard errors).
$^{\dagger}p < 0.10$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

experimental data contained 26,627 (87.9%) names that are most likely to be white, 2,752 (9.1%) names that are most likely to be Hispanic, 449 (1.5%) names that are most likely to be black, 416 (1.4%) names that are most likely to be Asian/Pacific Islander, and six names (< 0.1%) that are most likely to be American Indian/Alaskan native. None of the names was most likely to be classified as belonging to people who identify with two or more races.

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 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.

We report regressions similar to those in the previous section in Table 8. The conclusions are largely consistent between methods for identifying ethnicity. The control variables include dummy variables for ethnicity for both the donor and the teacher, but they do not include gender, as it was not inferable from the donor's name with the census method.

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 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 (Pelham et al. 2002, Jones et al. 2004). 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 the causal role of name letters in driving the outcomes, 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.

We tested for surname initial-letter effects within our name-mismatch (control) condition, rather than look for effects across the entire data set. We did so for two reasons. First, matching on surname initial letter was highly correlated with full-name matching, as all of those in the name-match condition also matched on initial letter. This led to difficulty interpreting regression coefficients due to multicollinearity. Second, past authors have argued that the effect in question is thought to be one that occurs below conscious awareness (Pelham et al. 2002, Jones et al. 2004). We have argued that sharing a full name with someone should capture conscious attention, and thus may not be evidence for an implicit process.

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 and reported in Tables 1–7. We present the results of this analysis in Table 9. 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.

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, these accounts predict 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 online appendix.

Table 8. Replication of Findings with Census Data

Variable name	Opened	Clicked	Clicked given opened	Donated	Donated given clicked	Donation amount (OLS)	Donation amount, given clicked (OLS)
Matching							
Name match	0.343	0.357	0.123	0.939	0.610	0.005	0.054
	(0.027)***	(0.055)***	(0.059)*	(0.366)*	(0.370)†	(0.002)**	(0.034)
Ethnicity match	0.027	0.303	0.319	19.848	15.271	–0.001	–0.013
	(0.050)	(0.110)**	(0.117)**	(689.96)	(3,028.4)	(0.003)	(0.068)
Ethnicity control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	–0.983	–3.276	–1.869	–26.913	–19.292	0.004	0.084
	(0.046)***	(0.187)***	(0.108)***	(690.0)	(3028.4)	(0.003)	(0.063)
N	30,297	30,297	9,492	30,297	1,740	30,297	1,740
Cox and Snell R^2	0.006666	0.002665	0.002274	0.000538	0.005837	0.000407	0.003842

Note. Unstandardized parameter estimates and (standard errors).
†$p < 0.10$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

Table 9. Name-Letter Regressions Among Non-Match Condition

Variable name	Opened	Clicked	Clicked given opened	Donated	Donated given clicked	Donation amount (OLS)	Donation amount, given clicked (OLS)
Matching							
First letter match	0.177	0.166	0.032	1.117	0.985	0.007	0.123
	(0.076)*	(0.156)	(0.167)	(0.789)	(0.836)	(0.004)†	(0.082)
Ethnicity match	–0.001	0.078	0.088	1.338	0.429	0.002	0.020
	(0.048)	(0.100)	(0.107)	(1.501)	(1.527)	(0.003)	(0.052)
Gender match	–0.069	–0.223	–0.195	–0.153	–0.520	0.000	0.000
	(0.072)	(0.171)	(0.182)	(0.912)	(1.028)	(0.004)	(0.092)
Country match	0.029	0.075	0.061	0.830	0.829	0.002	0.032
	(0.042)	(0.088)	(0.094)	(0.650)	(0.676)	(0.002)	(0.045)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	–1.012	–3.305	–1.877	–7.673	–4.127	0.007	0.168
	(0.081)***	(0.187)***	(0.197)***	(1.63)***	(1.579)**	(0.004)	(0.098)†
N	14,329	14,329	4,177	14,329	700	14,329	700
Cox and Snell R^2	0.001263	0.000655	0.002006	0.001421	0.029737	0.001136	0.039149

Note. Unstandardized parameter estimates and (standard errors).
†$p < 0.10$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

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, surname first-letter effects are thought to be a result of implicit egotism. That is, if a person has a less common name, that name should be more closely associated with the person's identity compared with someone with a very common name. This closer self-identity should also affect how closely one favors the name letter (Pelham et al. 2002, Jones et al. 2004, Pelham et al. 2005). Thus, we tested for interactive effects of name commonness with surname first letters. 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 online appendix.

6. Discussion and 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 small name-letter effect. Participants who did not share a full surname were more likely to open the email when the teacher shared the same surname initial 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, after implementing more rigorous controls.

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, name letters, and emails about people of the opposite gender may garner greater attention, while matching on both gender and ethnicity may foster feelings of similarity. Both attention and similarity can lead to increased charitable giving.

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. The discussion leads to avenues for future research 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.

6.1. Effectiveness

Did manipulating 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, and donate, and they donated more on average to teachers who shared their surname compared with 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. Across all of their email campaigns, their average open rate is about 20%, and they observe click rates between two and three percent (Penny 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% (Pay 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. Although 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 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."

Beyond full-name matches, we have 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 even larger effect than name matching for donations after the donor clicked the link. 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 from 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 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, though the limitations of research in the field prevent definitive conclusions. 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 and leading to more charitable behavior (Galak et al. 2011, Sudhir et al. 2016). 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 (Pelham et al. 2002, Jones et al. 2004, Pelham and Carvallo 2015; see also Simonsohn 2011a, b). Our results are consistent with these processes.

6.2.1. Attention. Open rates for the email may be the best evidence for an attentional mechanism. Consistent with the idea that names garner attention (Sahni et al. 2018), we found that emails with name-matched subject lines were opened more often. We also found higher open rates when potential donors were matched merely on the first letter of their surname. Thus, it is highly likely that these effects are at least partially attributable to attention, perhaps even mostly so, as conditional on clicking on the link, neither name matching nor sharing name letters seemed to raise the likelihood of donating by themselves.

We also found opposing forces for similarity on gender. First, all else equal, potential donors were more likely to open emails about teachers of the opposite gender (true for both male and female donors). As opposite genders attract greater attention (Maner et al. 2007), this first result is also consistent with an attention mechanism. This result is consistent with past field experiments where photos of attractive women led to better responses from men in a direct mail campaign (Bertrand et al. 2010).

Second, matching on both gender and ethnicity (independent of the effects of matching on one of these elements alone) also improved outcomes. This result is consistent with a study on secondary data where same genders encouraged microloans to would-be entrepreneurs (Galak et al. 2011), and may be better interpreted as fostering similarity, which we discuss in the next section.

One way to reconcile the past findings may be to examine 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 microlending platform (Galak et al. 2011), all observed parties are already attentive, and other processes may dominate. This hypothesis would require more direct testing to confirm.

Similar to full-name matching, we observed that matching on surname initial letters most strongly affected open rates. This suggests that name-letter effects may be related to attention. The original authors to document the name-letter effect have acknowledged this as a possibility (Jones et al. 2004). However, the role of attention may have been underappreciated previously, as the authors favored an explanation centered on "implicit egotism." More will be said on this topic when we discuss future research in Section 6.3.

6.2.2. Feelings of Closeness to Similar Others.

In addition to attention, our results are consistent with ideas about favoring similar others (Byrne 1971) and treating them more like members of a social group (Small and Simonsohn 2008, Galak et al. 2011). Phrased differently, similarity seems to reduce the social distance between people (Loewenstein and Small 2007). Consistent with this idea, matching on both ethnicity and gender fostered more favorable outcomes, above and beyond matching on name.

Comparing across dependent variables may also suggest that ethnicity matching may be relatively more impactful on actual donations, rather than open or click rates. Note that when potential donors click on a link in the email, they are brought to a project page on the DonorsChoose.org website, 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.

As discussed earlier, it may also be that matching on ethnicity and gender do not garner as much initial attention, but do have influence later in the donation funnel when effects may be driven by similarity. That being said, we do also find some evidence that ethnicity can affect even early stages of the funnel, as jointly matching on both gender and ethnicity was associated with higher open rates.

6.2.3. Alternative Explanations.

Although our results are consistent with process explanations centered on attention and preferential treatment of similar others, alternative 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 (Wattal et al. 2012, Song et al. 2016), allowing the positive effects on attention to be more pronounced. This could explain why older findings seem to be more negative (White et al. 2008, Wattal et al. 2012) than more recent ones (Sahni et al. 2018).

Another alternative explanation may be related to organizational competencies. We argued earlier that is was unlikely that the name-mismatch group suffered from a perception of being poorly matched. However, it may also be possible that DonorsChoose, by being able to craft such a charming and sophisticated email marketing campaign, signaled their competency to potential donors. There may be a positive effect from this signaling alone (Nelson 1974, Anand and Shachar 2009). Similarly, name-matched ads may simply have seemed more relevant to potential donors, which has been shown to boost ad effectiveness (Ansari and Mela 2003, Bleier and Eisenbeiss 2015).

6.3. Future Directions

Considering these potential causal mechanisms may also help us to hypothesize about when personalizing using similarity might help drive engagement with marketing communications (Sudhir et al. 2016, Sahni et al. 2018), and when it might be less effective or even backfire (Wattal et al. 2012). Although the effect of similarity generally leads to positive outcomes, people may respond differently to self-similar entities under threatening conditions (Jones et al. 2002, Brendl et al. 2005), or when the self-similar entity is otherwise undesirable (e.g., Alter 2009). For instance, in contrast to the findings of this study, a study by Burger et al. (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 reseller 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, Wattal et al. 2012, Sahni et al. 2018) 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 they wish to be more closely associated. Future work should directly test these hypotheses.

Future work might also reexamine name-letter effects, in which people prefer the letters of their own name compared with other letters of the alphabet (Nuttin 1985). Typically, name-letter effects are explained in terms of implicit egotism (Pelham et al. 2002, Jones et al. 2004)—an unconscious preference for stimuli that mirror or match elements of the self. Our results suggested that the role of attention in influencing these outcomes may be greater than previously thought. Specifically, potential donors were more likely to open an email about a person in need who shared the initial letter of the potential donor's own surname, but didn't show strong effects for outcomes that rely less heavily on attention, such as the decision of whether to donate conditional on having already clicked on a solicitation link in the email. In addition to this attention mechanism, we also discussed the possibility that people might respond to self-relevant stimuli because those stimuli signal an overlap in social identity (including ethnicity or nationality). These attentional and self-relevance effects might work together, but they may also operate differently depending on the stakes of the decision. When decisions have limited consequences, attentional mechanisms may be enough to influence outcomes, as observed in several laboratory studies (Jones et al. 2004, Brendl et al. 2005). In contrast, for choices with greater consequences, attention alone may not be sufficient, and effects may be driven more strongly by social closeness. Thus, researchers should be able to detect name-letter effects in secondary data (Jones et al. 2004, Anseel and Duyck 2008), but those effects may be weaker when researchers partial out variance associated with group membership based on ethnicity (as suggested by, for example, Simonsohn 2011a, b).

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 repeatedly leveraged this fundraising tactic with apparent success, 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

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.

Acknowledgments

The authors thank Weiyi Ng of the National University of Singapore for assistance with data analysis, and Katie Bisbee, Jasmine Penny, and Morgan Kazan of DonorsChoose for their collaboration in collecting the data.

Endnotes

[1] See https://aspredicted.org/5xp2f.pdf. The preregistration included details about the overall sample size, assignment to condition, and the primary analyses reported in Section 5.1. Other analyses were not explicitly preregistered.

[2] As reported in the online appendix, we also ran an analysis such that 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. The results are nearly identical.

[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.

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

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

References

Alter AL (2009) Scrutinize thy neighbor: Ingroup polarization inresponse to confirmed and violated interpersonal expectations. Dissertation, Princeton University, Princeton, NJ.

Anand BN, Shachar R (2009) Targeted advertising as a signal. *Quant. Marketing Econom.* 7(3):237–266.

Anderson BA, Laurent PA, Yantis S (2011) Value-driven attentional capture. *Proc. Natl. Acad. Sci. USA* 108(25):10367–10371.

Anderson ET, Simester DI (2004) Long-run effects of promotion depth on new vs. established customers: Three field studies. *Marketing Sci.* 23(1):4–20.

Anderson SP, Ciliberto F, Liaukonyte J, Renault R (2016) Push-me pull-you: Comparative advertising in the OTC analgesics industry. *RAND J. Econom.* 47(4):1029–1056.

Ansari A, Mela CF (2003) E-customization. *J. Marketing Res.* 40(2): 131–145.

Anseel F, Duyck W (2008) Unconscious applicants: A systematic test of the name-letter effect. *Psych. Sci.* 19(10):1059–1061.

Arora N, Dreze X, Ghose A, Hess JD, Iyengar R, Jing B, Joshi Y, et al. (2008) Putting one-to-one marketing to work: Personalization, customization, and choice. *Marketing Lett.* 19(3–4):305–321.

Awad NF, Krishnan MS (2006) The personalization privacy paradox: An empirical evaluation of information transparency. *Management Inform. Systems Quart.* 30(1):13–28.

Bargh JA (1982) Attention and automaticity in the processing of self-relevant information. *J. Personality Soc. Psych.* 43(3):425–436.

Bertrand M, Karlan D, Mullainathan S, Shafir E, Zinman J (2010) What's advertising content worth? Evidence from a consumer credit marketing field experiment. *Quart. J. Econom.* 125(1): 263–305.

Bleier A, Eisenbeiss M (2015) Personalized online advertising effectiveness: The interplay of what, when, and where. *Marketing Sci.* 34(5):669–688.

Braun M, Bonfrer A (2011) Scalable inference of customer similarities from interactions data using Dirichlet processes. *Marketing Sci.* 30(3):513–531.

Brendl CM, Chattopadhyay A, Pelham BW, Carvallo M (2005) Name letter branding: Valence transfers when product specific needs are active. *J. Consumer Res.* 32(3):405–415.

Burger JM, Messian N, Patel S, del Prado A, Anderson C (2004) What a coincidence! The effects of incidental similarity on compliance. *Personality Soc. Psych. Bull.* 30(1):35–43.

Byrne DE (1971) *The Attraction Paradigm* (Academic Press, New York).

Campbell MC, Kirmani A (2000) Consumers' use of persuasion knowledge: The effects of accessibility and cognitive capacity on perceptions of an influence agent. *J. Consumer Res.* 27(1): 69–83.

Chandler J, Griffin TM, Sorensen N (2008) In the "I" of the storm: Shared initials increase disaster donations. *Judgment Decision Making* 3(5):404–410.

Cherry EC (1953) Some experiments on the recognition of speech, with one and with two ears. *J. Acoustical Soc. Amer*. 25(5):975–979.

Cox DR, Snell EJ (1989) *The Analysis of Binary Data*, 2nd ed. (Chapman and Hall, London).

DellaVigna S, List JA, Malmendier U (2012) Testing for altruism and social pressure in charitable giving. *Quart. J. Econom.* 127(1):1–56.

Eastlack JOJ, Rao AG (1989) Advertising experiments at the Campbell Soup Company. *Marketing Sci.* 8(1):57–71.

Esterl M (2014) "Share a Coke" credited with a pop in sales: Marketing campaign that put first names on bottles reversed downward slide. *Wall Street Journal* (September 25), https://www.wsj.com/articles/share-a-coke-credited-with-a-pop-in-sales-1411661519.

Evergage (2018) 2018 trends in personalization. Accessed May 9, 2018, https://www.evergage.com/wp-content/uploads/2018/04/Evergage-2018-Trends-in-Personalization-Survey.pdf.

Friestad M, Wright P (1994) The persuasion knowledge model: How people cope with persuasion attempts. *J. Consumer Res.* 21(1): 1–31.

Galak J, Small D, Stephen AT (2011) Microfinance decision making: A field study of prosocial lending. *J. Marketing Res.* 48:S130–S137.

Gneezy U, Keenan EA, Gneezy A (2014) Avoiding overhead aversion in charity. *Science* 346(6209):632–635.

Goel S, Goldstein D (2013) Predicting individual behavior with social networks. *Marketing Sci.* 33(1):1–157.

Goldfarb A, Tucker C (2011) Online display advertising: Targeting and obtrusiveness. *Marketing Sci.* 30(3):389–404.

Guéguen N, Pichot N, Le Dreff G (2005) Similarity and helping behavior on the web: The impact of the convergence of surnames between a solicitor and a subject in a request made by email. *J. Appl. Soc. Psych.* 35:423–429.

Hauser JR, Urban GL, Liberali G, Braun M (2009) Website morphing. *Marketing Sci.* 28(2):202–223.

Jones JT, Pelham BW, Carvallo M, Mirenberg MC (2004) How do I love thee? Let me count the Js: Implicit egotism and interpersonal attraction. *J. Personality Soc. Psych.* 87(5):665–683.

Jones JT, Pelham BW, Mirenberg MC, Hetts JJ (2002) Name letter preferences are not merely mere exposure: Implicit egotism as self-regulation. *J. Experiment. Soc. Psych.* 38(2):170–177.

Khan R, Lewis M, Singh V (2009) Dynamic customer management and the value of one-to-one marketing. *Marketing Sci.* 28(6): 1063–1079.

Kim T, Barasz K, John LK (2019) Why am I seeing this ad? The effect of ad transparency on ad effectiveness. *J. Consumer Res.* 45(5): 906–932.

King J (2018) Consumers don't want personalization to get too personal. *eMarketer* (April 26), https://www.emarketer.com/content/consumers-don-t-want-personalization-to-get-too-personal.

Kramer T, Spolter-Weisfeld S, Thakkar M (2007) The effect of cultural orientation on consumer responses to personalization. *Marketing Sci.* 26(2):246–258.

Lambrecht A, Tucker C (2013) When does retargeting work? Information specificity in online advertising. *J. Marketing Res.* 50(5): 561–576.

List JA (2011) The market for charitable giving. *J. Econom. Perspect.* 25(2):157–180.

Loewenstein G, Small DA (2007) The scarecrow and the tin man: The vicissitudes of human sympathy and caring. *Rev. General Psych.* 11(2):112–126.

Maner JK, Gailliot MT, DeWall CN (2007) Adaptive attentional attunement: Evidence for mating-related perceptual bias. *Evolution Human Behav.* 28(1):28–36.

Motoki K, Saito T, Nouchi R, Kawashima R, Sugiura M (2018) Tastiness but not healthfulness captures automatic visual attention: Preliminary evidence from an eye-tracking study. *Food Quality Preference* 64:148–153.

Murthi BPS, Sarkar S (2003) The role of the management sciences in research on personalization. *Management Sci.* 49(10):1344–1362.

Nelson P (1974) Advertising as information. *J. Political Econom.* 82(4): 729–754.

Newman RS (2005) The cocktail party effect in infants revisited: Listening to one's name in noise. *Developmental Psych.* 41(2): 352–362.

Nuttin JM (1985) Narcissism beyond Gestalt and awareness: The name letter effect. *Eur. J. Soc. Psych.* 15(3):353–361.

Oates K, Wilson M (2002) Nominal kinship cues facilitate altruism. *Proc. Biol. Sci.* 269(1487):105–109.

Pay K (2017) Email marketing & beyond: Global industry benchmarks. Accessed July 7, 2017, https://www.getresponse.com/resources/reports/email-marketing-and-beyond-global-industry-benchmarks-2017.

Pelham BW, Carvallo M (2015) When Tex and Tess carpenter build houses in Texas: Moderators of implicit egotism. *Self Identity* 14(6):692–723.

Pelham BW, Carvallo M, Jones JT (2005) Implicit egotism. *Current Directions Psych. Sci.* 14(2):106–110.

Pelham BW, Mirenberg MC, Jones JT (2002) Why Susie sells seashells by the seashore: Implicit egotism and major life decisions. *J. Personality Soc. Psych.* 82(4):469–487.

Penny J (2017) Personal communication, July 26.

Ratcliff C (2015) How digital transformation improved Marie Curie's marketing strategy. *Econsultancy* (January 27), https://econsultancy.com/blog/66018-how-digital-transformation-improved-marie-curie-s-marketing-strategy/.

Rossi PE, McCulloch RE, Allenby GM (1996) The value of purchase history data in target marketing. *Marketing Sci.* 15(4):321–340.

Sahni NS (2015) Effect of temporal spacing between advertising exposures: Evidence from online field experiments. *Quant. Marketing Econom.* 13(3):203–247.

Sahni NS, Wheeler SC, Chintagunta P (2018) Personalization in email marketing: The role of noninformative advertising content. *Marketing Sci.* 37(2):236–258.

Sahni NS, Zou D, Chintagunta PK (2017) Do targeted discount offers serve as advertising? Evidence from 70 field experiments. *Management Sci.* 63(8):2688–2705.

Simmons JP, Nelson LD, Simonsohn U (2012) A 21 word solution. *Dialogue: Official Newslett. Soc. Personality Soc. Psych.* 26(2): 4–7.

Simonsohn U (2011a) Spurious? Name similarity effects (implicit egotism) in marriage, job, and moving decisions. *J. Personality Soc. Psych.* 101(1):1–24.

Simonsohn U (2011b) Spurious also?: Name-similarity effects (implicit egotism) in employment decisions. *Psych. Sci.* 22(8):1087–1089.

Small DA, Simonsohn U (2008) Friends of victims: Personal experience and prosocial behavior. *J. Consumer Res.* 35(3):532–542.

Song JH, Kim HY, Kim S, Lee SW, Lee JH (2016) Effects of personalized email messages on privacy risk: Moderating roles of control and intimacy. *Marketing Lett.* 27(1):89–101.

Sudhir K, Roy S, Cherian M (2016) Do sympathy biases induce charitable giving? The effects of advertising content. *Marketing Sci.* 35(6):849–869.

Summers CA, Smith RW, Reczek RW (2016) An audience of one: Behaviorally targeted ads as implied social labels. *J. Consumer Res.* 43(1):156–178.

Tajfel H, Turner J (1979) An integrative theory of intergroup conflict. Austin WG, Worchel S, eds. *The Social Psychology of Intergroup Relations* (Brooks/Cole, Monterey, CA), 33–37.

Tucker CE (2014) Social networks, personalized advertising, and privacy controls. *J. Marketing Res.* 51(5):546–562.

Urban GL, Liberali GG, MacDonald E, Bordley R, Hauser JR (2014) Morphing banner advertising. *Marketing Sci.* 33(1):27–46.

Wattal S, Telang R, Mukhopadhyay T, Boatwright P (2012) What's in a "name"? Impact of use of customer information in email advertisements. *Inform. Systems Res.* 23(3-part-1):679–697.

White TB, Zahay DL, Thorbjørnsen H, Shavitt S (2008) Getting too personal: Reactance to highly personalized email solicitations. *Marketing Lett.* 19(1):39–50.

Zhang J (2011) The perils of behavior-based personalization. *Marketing Sci.* 30(1):170–186.

Zhang J, Krishnamurthi L (2004) Customizing promotions in online stores. *Marketing Sci.* 23(4):561–578.