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What Age Is in a Name?

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Abstract: Social scientists often describe fictional people in survey stimuli using first names. However, which name a researcher chooses may elicit nonrandom impressions, which could confound results. Although past research has examined how names signal race and class, very little has examined whether names signal age, which is a highly salient status characteristic involved in person construal. I test the perceived demographics of 228 American names. I find that most strongly signal age, with older-sounding names much more likely to be perceived as white than as black. Furthermore, participants' perceptions of the age of a name poorly match with the true average birth year of people with that name, suggesting that researchers cannot simply use birth records as a proxy for perceived age. To assist researchers in name selection, I provide a set of candidate names that strongly signal a matrix of combined age, race, and gender categories.

Keywords: names; age; perception; vignettes; audit studies; survey methods

VIGNETTES describing fictional people are used in surveys and other forms of data collection to test myriad psychological, political, and sociological phenomena. The "same" fictional people have shown up in commonly used survey questions and stimuli for decades across many social science disciplines, such as "Donald" in paradigms of social priming (Higgins, Rholes, and Jones 1977; Mussweiler and Damisch 2008; Srull and Wyer 1979), "Katie Banks" in research on perspective-taking (Batson 1991; Myers, Laurent, and Hodges 2014), and "Linda" in research on the conjunction fallacy (Charness, Karni, and Levin 2010; Tversky and Kahneman 1983). Researchers studying labor market discrimination have used names on fictional resumes or employee fact-sheets to test whether discrimination operates in hiring and promotion across status characteristics including race (Bertrand and Mullainathan 2004), gender (Moss-Racusin et al. 2012), criminal history (Pager 2003), and parenthood (Correll, Benard, and Paik 2007).

However, names are not randomly distributed across the human population, and first names can signal demographic categories. Names are generally chosen for people by their parents through deeply entrenched and meaningful cultural processes (Alford 1987; Elchardus and Siongers 2011; Lieberson 2000) and can therefore signal many demographic features of a person, including their gender category, country of origin, ethnicity, class, and race (Gaddis 2017a, 2017b; Goldstein and Stecklov 2016; Lieberson, Dumais, and Baumann 2000). The signaling power of names suggests that the particular name used in a survey stimulus may cause research participants to have systematic impressions about the fictional person being discussed. If ignored, those impressions may influence participant behavior in ways that bias the interpretation of results.

At the same time, using names in vignettes is important and valuable for two reasons. First, it helps give ecological validity to data collection: it may be easier

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for participants to engage if they can imagine a real person behind the vignette (Hughes and Huby 2004), and in the case of labor market audit studies, listing a name on a job application is necessary for the application to be considered at all. Second, the signaling power of names can be explicitly harnessed to signal theoretically salient features of individuals such as gender (Moss-Racusin et al. 2012; Castilla and Benard 2011), race (Bertrand and Mullainathan 2004; Gaddis 2017a, 2017b), and class (Barlow and Lahey 2018; Elchardus and Siongers 2011; Gaddis 2017a). Some scholars interested in differences based on a target's race have used *only* name difference to signal the race category membership of a fictional person (Bertrand and Mullainathan 2004; Correll et al. 2007; Gaddis 2015). Their name selection is based on a significant body of work showing how names signal race and class (Barlow and Lahey 2018; Crabtree and Chykina 2018; Gaddis 2017b, 2017a; Goldstein and Stecklov 2016).[1]

Despite growing awareness of how names signal group membership, very little research has examined how names signal age. This is troubling because age is a crucial ordering principle of social interaction; age perception happens within milliseconds of interacting with a new person (Brewer and Lui 1989), and age schemas and stereotypes are salient and impact behavior (Boyd and Dowd 1988; Fiske et al. 2018; Kite, Deaux, and Miele 1991; Posthuma and Campion 2009). The sense an actor has about another person's age can change the overall meaning of the interpersonal interaction, including status processes (Kelley, Soboroff, and Lovaglia 2017; Laz 1998). Furthermore, age discrimination is significant and well documented, particularly in the labor market (Adams 2002; Chiu et al. 2001; Neumark, Burn, and Button 2016; Rosen and Jerdee 1976), and can be triggered through signals of age other than a stated chronological age (Derous and Decoster 2017). The way a research participant perceives and makes sense of a fictional person's age, then, may very well impact the way they interpret that person and could even change the way they respond behaviorally. Results from any research that uses names in vignettes may not generalize in the way that study authors have claimed if the name they selected signals age and the behavioral response to the stimuli interacts with the perceived age of the hypothetical person.

In the small number of cases where there has been sensitivity to controlling for age signaling, the current best-practice protocol for name selection involves picking names that were relatively popular at a given point in time; however, considering name popularity only within a short historical time period fails to select names that on the whole represent a particular age. For example, Bertrand and Mullainathan (2004) created a name list that has since been used by many researchers (e.g., Correll et al. 2007) by examining data from Massachusetts birth certificates from 1974 to 1979 to select names that were highly likely to be given to either white or black babies. Similarly, in one of the largest studies to date on the race and class signaling of names, Gaddis (2017b, 2017a) used New York State birth records to select names from the early 2000s that were highly likely to be given to either black, Hispanic, or white babies. In both these studies, the researchers then tested whether the names signaled race (and in Gaddis' case, also class) but did not ask participants about whether the names were associated with particular ages. This selection method is clean and systematic if the researcher wants names that were associated with

demographic groups *at a certain point in history*, such as the mid-1970s or early 2000s. However, it is possible that those same names were even more popular at a different time and therefore that the name overall does not signal birth within that particular window. It also leaves open the possibility that names that have certain race, class, and gender associations at one point in time may have different meanings for babies born decades earlier or later. For example, as I will show later, I find that the black-signaling names in Bertrand and Mullainathan (2004) were perceived by my participants as significantly younger than the white-signaling names were.

Furthermore, real-world variation in naming behavior may be different from people's *perceptions* of the age associated with a name. Just because a randomly selected American named Linda is likely to be older than a randomly selected American named Jennifer (as birth record data would suggest) doesn't mean that a participant reading a vignette may perceive (consciously or unconsciously) "Linda" and "Jennifer" as different ages. It is reasonable to assume that most people may only have a vague sense of when names were most popular. What matters for validity of using names in vignettes is therefore not some "reality" of how old the name is, but what participants perceive the age of a name to be. Given research on differences in age perception processes among younger and older actors (Chopik and Giasson 2017; Giasson et al. 2017), it is also possible that names signal age differently for different types of participants.

Research Questions

1. Do names signal age?
2. Do name-based perceptions of age interact with perceptions of gender, race, and class?
3. Do participants within different demographic categories perceive the age of names in systematically different ways?
4. Can researchers use birth record data on the real-world age distribution of names as a proxy for the perceived age of a name?

I answer these questions by testing whether and how 228 American names signal age through an online experiment with a sample of Amazon Mechanical Turk workers. Across this large sample of names intentionally selected to vary across age, race, and gender, I find that names are strong signals of age, in addition to race and gender, but seem to be weak signals of class (as measured through perceived parental education). Age, race, and parental education perceptions are correlated, in that older-sounding names are more likely to be perceived as white (compared with black) and as having highly educated parents. There are no names in my sample that signal old age and blackness, despite my attempt to include such names in my sample. Older participants tend to perceive names as older, whereas black participants (compared with white) and men participants (compared with women) tend to perceive names as slightly younger. Furthermore, I find that people's perceptions of the age associated with a name often do not match well

with what a researcher might assume based on average birth year from birth record data. In particular, names that have been popular over a longer period of time, such as Anna, Catherine, Charlie, and Carrie, are perceived as younger than they truly are in the population. Finally, I provide a set of candidate names that signal intersecting identities across age, gender, and race that can serve as a starting point for researchers wishing to control for age in their name selection.

Methods

To test the extent to which names signal age, race, gender, and class, I fielded a large online survey experiment that asked survey participants about their impressions and perceptions of particular names.

Selecting Names to Test

I selected 228 American names drawn from a variety of sources designed to capture variance across race (black/white), gender (man/women), and age. In order to obtain a sample of names that contained high numbers of both white and black names, I selected the top 30 white-signaling names and top 30 black-signaling names, as measured by rate of congruence between racial perception and birth record data, from Gaddis (2017). Next, I used birth record data from the Social Security Administration (SSA) on frequencies of babies born to every name (that had five or more babies with that name) each year from 1880 to 2018.[2] I selected 90 names with a high probability of being age-typed by first searching for names whose mean and mode birth year was within the same decade (1930–1939, 1940–1949, 1950–1959, 1960–1969, 1970–1979, 1980–1989, 1990–1999, 2000–2009, 2010–2018), and then selecting the 10 names from each decade that had the smallest standard deviation in number of babies per year to get highly time-specific names. I also used SSA data to select names with a low probability of being age-typed by choosing names that had more than 500,000 babies born to the name (127 names of the 98,400 in SSA's database) *and* a standard deviation of more than 25 years, for 31 additional names. In an attempt to increase the likelihood of finding names that signaled older ages and blackness, I tested the 21 names that Cook, Logan, and Parman (2014) found were given disproportionately to black men from 1900 to 1920. Finally, I chose 63 names from five influential studies on labor market discrimination (Bertrand and Mullainathan 2004; Castilla and Benard 2011; Gaddis 2015; Rivera and Tilcsik 2016; Tilcsik 2011) and nine names from seven popular stimuli from research in social psychology (Baron-Cohen, Leslie, and Frith 1985; Batson 1991; Darley and Gross 1983; Higgins et al. 1977; Kohlberg 1981; Moss-Racusin et al. 2012; Tversky and Kahneman 1983).[3] After removing duplicates from these lists, I was left with 228 names in my sample (see the online supplement for a full list of names and their sources).

Note that my goal here was not to create a representative set of American names. Rather, it was to select names that would be useful for researchers: names that had been used in existing research and names that had a high probability of signaling age, race, and gender such that researchers may be able to use them in future

research. The primary dimensions of variation I was interested in capturing were age, race (limited to white and black), and gender. Also, I limited this study to first names; although last names have been found to influence racial and class perceptions (Crabtree and Chykina 2018; Gaddis 2017a), I expected that last names would be weaker signals of age given patrilinear naming conventions in the United States.[4]

Survey Sample

I recruited participants through Amazon Mechanical Turk (mTurk), a widely used online platform for research across the social sciences (including in past name-signaling studies, such as Gaddis 2017a, 2017b). mTurk is an ideal sample for this research because it is resource-efficient, ideal for measuring broad societal patterns of person perception, and has been found to have a high quality of data for similar types of research questions (Weinberg, Freese, and McElhattan 2014). I restricted my sample to mTurk workers who were living in the United States and had more than 500 approved past tasks (i.e., were likely experienced and high-quality survey participants). Pretesting suggested that the survey took an average of 12 minutes, and therefore I paid participants $1.45 to complete the survey (12 minutes at $7.25 federal minimum wage), which is an above-market rate on the mTurk platform.

I recruited 978 participants for this study. Of these, 830 completed all demographic questions and, for at least one name, had completed all perception questions and passed a manipulation check asking them to retype the name they just had answered questions about. I use ratings from these 830 participants as my analytical sample, although all results are similar if I include the entire sample of observations. Participants in the analytical sample varied from 19 to 78 years old, with the average chronological age being 37 years. Seventy-four percent of participants identified as white (alone or in combination with another race), and 14 percent identified as black (alone or in combination with another race). Forty-seven percent identified as a woman and 53 percent as a man. Sixty percent of participants indicated that they had obtained a bachelor's degree or higher, and 96 percent of participants were born in the United States.

Survey Procedure

At the beginning of the survey, participants were told, "we are interested in the age, gender, race, and class categories associated with common American names." They then saw a series of 10 different names (randomly selected from the 228 names) and were asked about their perceptions of a person based on just the name.[5] Participants were told explicitly that "your initial impressions are fine. Even if you are not very familiar with a name, please answer with your best guess."

Age perceptions. For each name, participants first answered three questions about perceived age. They were told to "please imagine an average person named [name]. Try to be as specific as possible in thinking about what type of person [name] is most likely to be." The first question was a broad subjective age question that asked, "How young or old is the person you imagined named [name]?" with a slider whose poles were labeled "very young" and "very old" (slider was otherwise unlabeled

in words or numbers). Next, participants responded to the question "How young or old is [name] relative to you?" with five response options ("much younger than me" to "much older than me"). Finally, participants were asked "How many years old is [name]? Please type a number. Your best guess is fine." I excluded responses that were more than 100 years from my analytical sample because of the likelihood that they were created by bots or other low-quality participants. Responses to the three age perception questions were highly correlated ($r = 0.982$ and 0.966, both $p < 0.001$). For clarity, I focus on responses of the third question, about perceived chronological age, for this article; however, all patterns reported are similar when analyzed based on any of the three age perception questions. At the end of each age perception section, participants also indicated how "confident are you that an average person named [name] has the characteristics you just indicated?" on a four-item scale from "not at all confident" to "very confident." Levels of confidence were moderate (average confidence across names was 2.88 out of 5) and relatively consistent across names (see the online supplement for full results across all names tested).

Gender, race, and parental education perceptions. After responding to the three age questions, respondents were asked about the gender and race they thought "a person with the name [name] is most likely to be" and then the amount of education they thought "the parents of a person with the name [name] likely completed." Amount of education completed is a standard proxy for social class; I measure perceived class through perceived parental education because the amount of education a person has completed is confounded with age (i.e., teenagers are unlikely to have completed college, etc.), and because this method matches with existing studies on the class signaling of names (e.g., Barlow and Lahey 2018). There were separate five-item scales (from "extremely unlikely" to "extremely likely") for two gender categories ("Woman or girl" and "Man or boy"), six race categories (white, black, Hispanic/Latino, Asian, Native American or Alaska Native, and Native Hawaiian or Pacific Islander; I focus on white and black here), and four education categories (less than high school, high school graduate, some college, or college graduate; I collapse these into no college vs. attended college). Finally, respondents were asked an open-ended question: "Are there any other impressions you have about the name [name]? Please share any other associations or thoughts you have."

Respondent demographics. After participants responded to the above questions for each of the 10 names assigned them, I asked them several questions about their own demographics, including their chronological age, birth year, race identification, gender identification, and whether they were born in the United States. I excluded 21 participants who listed a birth year that was more than one year different from their reported chronological age (calculated at 2019 or 2020) and then use reported chronological age as the primary measure of respondent age.

The survey ended with follow-up questions about how clear the survey questions were. Seventy-eight percent of participants indicated that the survey questions were either "somewhat" or "extremely" clear. Responses from an open-ended feedback text box at the end indicate that most participants found the survey engaging and interesting to complete.

Analysis

Because participants were randomized into name conditions, each name had between 18 and 70 responses (median = 36). I analyzed most results aggregated at the name level, except analyses focused on associations of age perceptions with participant demographics, which I analyzed at the perception level and for which I clustered standard errors at the participant level (each participant had 1–10 observations, depending on how many names they successfully responded to). In name-level analyses, I used raw averages of responses to perception questions for each name. For perceptions of gender, race, and parental education, I used the overall average reported likelihood that a name is associated with each category of interest. For perceptions of parental education, I created a similar measure but collapsed across less than high school and high school degree, as well as across some college and college degree, to get a two-category class measure (no college vs. attended college).

For perceptions of gender, race, and parental education, I also created a single score that represents the average difference in perceived likelihood of the two primary categories of interest (white vs. black; woman vs. man; did not attend college vs. attended college). For example, for the race score, for each perception I subtracted the reported likelihood that the name belongs to a black person from the reported likelihood that the name belongs to a white person. I then averaged across all observations to get an average score per name.[6]

Results

The 228 names I tested varied significantly in their perceived age. The name that was perceived as oldest among the 228 names I tested was "Deloris": on average, participants reported that an average person with this name was likely to be 67 years old. The name that was perceived as youngest was "Cayden," which was on average perceived as 16 years old. Mean and median age perceptions were similar to each other across all names (suggesting that distributions of responses were normally distributed), as were results across all three measures of age (see Methods, above). Monte Carlo permutations of the ratings indicate that the variance among the different means is more than 10 times what one would expect by chance alone (observed variance in means = 100.7 years, estimated variance in means by chance alone = 9.0 years based on one million permutations; $p < 0.001$). Names that were perceived as older tended to have higher variance in age perception (correlation between average and standard deviation in chronological age perception = 0.6163; $p < 0.001$) but also were associated with significantly higher levels of confidence in age perception (correlation between average chronological age perception and reported confidence [four-point scale] = 0.3275; $p < 0.001$). Table 1 lists the mean and standard deviation in perceived chronological age for all 228 names.

The names tested also consistently signaled gender and race and weakly signaled parental education. As Figure 1(a) shows, most names were perceived as very likely to be given to either a man or a woman, with low likelihood for the other category; many names have a three-point or greater difference (out of a five-point scale) in

Table 1: Mean perceived chronological age of 228 names

Name	Perceived age	Name	Perceived age	Name	Perceived age	Name	Perceived age
Cayden	16.4 (9.1)	Kevon	25.9 (8.2)	Katina	29.4 (14.1)	Terell	32.1 (11.1)
Zayden	17.0 (10.5)	Hannah	26.2 (6.9)	Kaitlin	29.6 (10.4)	Elijah	32.4 (14.0)
Jaiden	20.0 (6.2)	Kenya	26.3 (9.9)	DeShawn	29.6 (7.9)	Jermaine	32.4 (12.2)
Brynlee	20.2 (12.9)	Alexus	26.4 (12.0)	Hakim	29.7 (11.8)	Latonya	32.5 (10.3)
Jadyn	20.7 (7.6)	Logan	26.8 (13.1)	Latrell	30.0 (11.1)	Jake	32.8 (9.7)
Addyson	20.9 (12.2)	Tasha	27.2 (6.0)	Isaiah	30.1 (14.7)	Tammi	32.9 (13.8)
Kaydence	21.1 (9.5)	Aisha	27.2 (8.2)	Jamal	30.1 (7.4)	Tyrone	33.1 (10.8)
Jayden	21.3 (8.2)	Tanisha	27.2 (6.1)	Allison	30.1 (9.2)	Brandy	33.3 (8.2)
Jalen	21.6 (8.9)	Devonte	27.3 (6.7)	Latasha	30.2 (7.2)	Lamar	33.3 (11.0)
Janiyah	22.1 (10.0)	Cody	27.4 (7.9)	Luke	30.4 (10.1)	Sarah	33.8 (11.4)
Londyn	22.8 (13.1)	Keisha	27.4 (7.0)	King	30.4 (22.1)	Madeline	33.8 (17.9)
Janiya	22.9 (8.7)	DaShawn	27.5 (9.3)	Katie	30.5 (10.0)	Presley	33.8 (21.7)
Precious	23.0 (7.7)	Presly	27.6 (15.6)	Misty	30.5 (12.3)	Anna	33.9 (11.1)
Jayvon	23.5 (7.7)	Caleb	27.7 (13.6)	Tamika	30.5 (9.8)	Kareem	33.9 (11.8)
Nevaeh	23.6 (14.1)	Staci	27.8 (9.6)	Beckett	30.6 (18.0)	Seth	34.0 (12.0)
Aniyah	23.6 (7.9)	Denisha	27.8 (9.8)	Brandi	31.2 (10.3)	Prince	34.0 (16.4)
Ciera	23.8 (7.4)	Ethan	27.8 (11.2)	Shanice	31.2 (8.4)	Brett	34.3 (10.1)
DaQuan	23.9 (9.1)	Nia	27.9 (11.7)	Lesa	31.3 (13.8)	Sheena	34.4 (9.5)
Kadence	24.1 (11.5)	Chelsey	28.2 (8.0)	Brandie	31.3 (11.2)	Darnell	34.5 (9.3)
Adalynn	24.1 (17.2)	Connor	28.2 (14.0)	Tyra	31.4 (12.2)	Brad	34.6 (9.9)
Tayler	24.3 (7.2)	Aubrey	28.3 (12.7)	Emily	31.5 (11.4)	Julia	34.8 (12.2)
Iker	24.4 (21.4)	Kristen	28.3 (9.1)	Erica	31.5 (7.3)	Amy	34.8 (8.0)
Cierra	24.5 (6.6)	Ashanti	28.5 (7.5)	Yahir	31.5 (12.2)	Everly	34.8 (23.0)
Brittani	24.6 (7.7)	Emma	28.5 (14.0)	Rasheed	31.6 (9.1)	Traci	34.9 (11.1)
Hunter	24.6 (11.5)	Tremayne	28.8 (14.3)	Tiffany	31.6 (8.2)	Jennifer	34.9 (7.6)
Keyana	24.7 (6.0)	D'Andre	28.8 (9.3)	Alonzo	31.7 (12.2)	Kim	35.0 (7.7)
Katlyn	24.9 (9.3)	Keyshawn	29.0 (13.3)	Brendan	31.9 (10.0)	Latoya	35.1 (11.2)
Deja	24.9 (8.7)	DeAndre	29.1 (5.7)	Lakisha	31.9 (7.7)	Booker	35.4 (14.0)
Khloe	25.4 (8.8)	Krystle	29.3 (7.3)	Ebony	32.0 (11.4)	Isaac	35.4 (13.8)

Each name was ranked by 18 to 70 participants. Standard deviations are in parentheses.

Table 1 continued

Name	Perceived age	Name	Perceived age	Name	Perceived age	Name	Perceived age
Andrew	35.7 (10.0)	Scott	39.6 (9.0)	Sherri	44.7 (10.6)	Patti	50.6 (13.9)
Tammie	35.8 (12.3)	Jay	39.9 (16.0)	Samuel	45.2 (15.3)	Purlie	50.8 (27.8)
Tonya	35.8 (8.4)	Maria	40.1 (14.1)	Luann	45.5 (16.0)	Frank	51.2 (16.2)
Dustin	35.9 (14.7)	Titus	40.5 (22.5)	Laurie	45.5 (16.5)	Anne	51.3 (14.9)
Molly	36.3 (16.1)	Ambrose	40.7 (19.5)	Edward	46.1 (15.7)	Abraham	51.8 (19.7)
Vicki	36.3 (13.1)	Vickie	40.8 (14.3)	Marie	46.1 (13.4)	Evelyn	51.8 (22.0)
Tracey	36.5 (15.0)	Jack	41.3 (12.6)	Master	46.4 (22.0)	Alice	52.0 (21.1)
Heidi	36.7 (14.7)	Michael	41.4 (12.4)	Rhonda	46.8 (10.3)	Carole	52.2 (15.7)
Anthony	36.7 (12.4)	William	41.8 (11.1)	Geoffrey	47.1 (17.6)	George	52.2 (17.0)
Laura	36.9 (10.6)	Perlie	42.0 (30.0)	Debra	47.2 (13.5)	Freeman	52.5 (19.1)
Tricia	37.2 (14.8)	Katherine	42.3 (14.9)	Louella	47.6 (23.3)	Arthur	52.8 (19.0)
Jodi	37.3 (14.1)	Peter	42.4 (13.9)	Hilary	48.1 (16.5)	Barbara	52.9 (17.2)
Joseph	37.5 (14.2)	Meredith	42.6 (12.1)	Charles	48.2 (14.4)	Delbert	53.9 (19.0)
Carrie	37.7 (11.8)	Claire	42.9 (19.1)	Leroy	48.7 (17.1)	Moses	54.6 (19.7)
James	37.8 (13.5)	Thomas	43.1 (11.6)	Cathy	48.7 (13.2)	Phyllis	54.7 (21.2)
Kathi	38.0 (13.6)	John	43.2 (13.3)	Pearlie	48.7 (29.7)	Joan	55.7 (17.0)
Israel	38.0 (14.1)	Ann	43.3 (11.1)	Linda	48.8 (13.3)	Melva	57.0 (20.8)
Lisa	38.3 (11.4)	Tammy	43.3 (12.6)	Heinz	49.2 (24.5)	Walter	57.0 (16.2)
Tracie	38.3 (11.2)	Neil	43.4 (12.0)	Patricia	49.2 (16.7)	Margaret	57.1 (15.9)
Matthew	38.4 (11.4)	Sally	43.4 (18.0)	Carol	49.2 (15.7)	Donald	57.6 (15.8)
Elizabeth	38.6 (15.1)	Ronny	43.5 (15.1)	Robert	49.2 (11.3)	Earnestine	59.1 (25.3)
Todd	38.6 (12.6)	Cheryl	43.8 (12.2)	Bettye	49.3 (24.7)	Betty	59.5 (20.1)
David	38.6 (10.6)	Lori	43.9 (11.4)	Pat	49.3 (15.4)	Abe	59.8 (19.9)
Charlie	38.6 (16.1)	Benjamin	43.9 (13.8)	Raymond	49.3 (15.5)	Patsy	61.6 (10.8)
Kay	38.6 (15.6)	Pam	44.0 (11.5)	Dudley	49.6 (19.8)	Geraldine	62.6 (20.6)
Catherine	38.7 (15.2)	Percy	44.5 (22.5)	Judith	49.7 (17.4)	Dick	62.7 (12.0)
Greg	38.8 (11.6)	Jill	44.5 (12.8)	Deborah	50.3 (9.3)	Dolores	62.9 (19.0)
Lesly	39.2 (17.6)	Doug	44.6 (11.0)	Henry	50.4 (16.2)	Deloris	65.6 (18.8)

Each name was ranked by 18 to 70 participants. Standard deviations are in parentheses.

likelihood of being perceived as one gender category compared with the other. The exception to this gender polarization was six names that were perceived as having relatively equal likelihood (Jalen, Pat, Presley, Presly, Jadyn, and Tayler), as well as several more that, though still very gendered, were still somewhat androgynous (i.e., on average less than a two-point difference, out of a five-point scale, in likelihood by gender category), including Londyn, Addyson, Kay, Kadence, Cayden, Yahir, Zayden, Jayden, Tremayne, Beckett, Charlie, and Ambrose. As the scatterplot shows, most of these androgynous names were also perceived as relatively young.

For race, as Figure 1(b) shows, the likelihood that names were associated with blackness or whiteness was less polarized than for gender, although many names did still consistently signal whiteness (e.g., Hunter, Emily, Heidi, Dick, and Jill) and blackness (e.g., DeAndre, DaQuan, Keyshawn, Devonte, and Lakisha). Several names were perceived on average has having equal likelihoods of being black and white, including Ciera, Purlie, Brandi, and Elijah. Notably, there are almost no names that strongly signal blackness and old age, as shown in the empty bottom-right side of the scatterplot in Figure 1(b). The only name that was on average seen as more than one point more likely to be black than white and more than 40 years old was Leroy.

As shown in Figure 1(c), names most weakly signaled parental education, with the highest-class-sounding names (Hannah, Meredith, Madeline, Connor, and Elizabeth) and the lowest-class-sounding names (Ciera, Tremayne, Precious, Perlie, and Terell) still only moderately different in reported likelihood that the person's parent went to college. This weak result is contrary to prior research findings on the class signaling of names. For full results across names and all gender, race, and parental education categories, see the online supplement.

Statistical analyses confirmed these associations between age, race, gender, and class. Several of the dimensions of perception were correlated, including race and age (older names were more likely to be seen as white, and younger names were more likely to be seen as black; corr $= 0.37$, $p < 0.001$), education and age (older names were more likely to be seen as having parents who went to college, and younger names were more likely to be seen as having parents who didn't go to college; corr $= -0.27$, $p < 0.001$), and, replicating Barlow and Lahey (2018), race and education (whiter names were seen as having parents who went to college, and blacker names were seen as having parents who didn't go to college; corr $= -0.67$, $p < 0.001$). Gender perceptions were not strongly correlated with age, race, or education. Table 2 shows results from an ordinary least squares regression predicting the average age perception of a name by other features of that name, including the perceived race, gender, and parental education. Regression results indicate that the association between perceived parental education and age was driven by a common association with perceived race (see models 1 and 3 in Table 2), further suggesting that the names in my sample were truly weak signals of parental education.

Overall, these results suggest that (1) the perceived age of a hypothetical person does vary based on just the first name, (2) older names were significantly more likely to be seen as white than as black, and (3) names in my sample weakly signaled parental education.

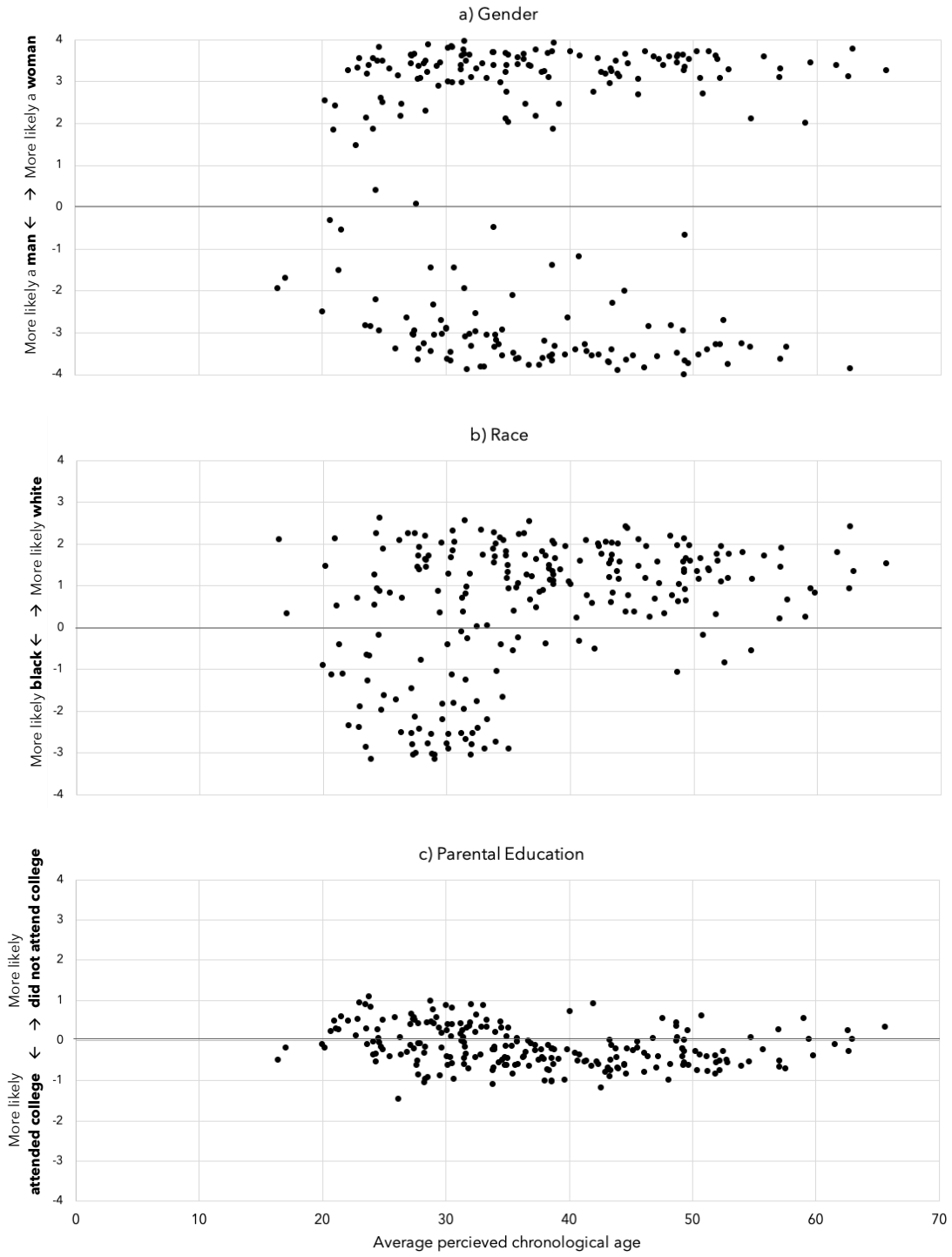

Figure 1: Chronological age perceptions by (a) gender, (b) race, and (c) parental education perceptions of 228 names. The *y* axis of each is the average difference in reported likelihood that the name belongs to a person in each category.

Table 2: Ordinary least squares regression predicting the age perception of a name by other perceived name characteristics (name level)

	Model 1	Model 2	Model 3
Confidence in age perception (four-point scale)	18.062†	18.071†	15.655†
	(3.977)	(3.994)	(3.949)
Perceived gender (average relative likelihood that person is a woman compared with a man—each on five-point scale)		−0.007	−0.223
		(0.206)	(0.210)
Perceived race (average likelihood that person is white compared with black—each on five-point scale)			2.006†
			(0.557)
Perceived parental education (average relative likelihood that parent of person with name did not go to college compared with likelihood they did go to college—each on five-point scale)	−4.537†	−4.531†	−0.153
	(1.314)	(1.331)	(1.778)
Constant	−15.377	−15.397	−8.609
	(11.389)	(11.430)	(11.295)
R^2	0.152	0.152	0.199

Note: Sample is 228 names, each with data averaged across several dozen respondents. Standard errors in parentheses. † $p < 0.01$; ∗ $p < 0.05$.

Associations with Participant Characteristics

Are participants' demographics associated their perceptions of the age of names? Table 3 shows results from a linear regression predicting the average perceived chronological age of a name based on the age, race, gender, education, and nativity (U.S. vs. foreign born) of the respondent (standard errors are clustered at the respondent level).[7] Across more than 7,800 name perceptions completed by 830 respondents, older participants tended to type in older ages of names: on average, one year older in chronological age was associated with 0.228 more years in perceived age of a name ($p < 0.001$). This suggests a relatively large difference in age perception by respondent age: each five-year increase in respondent age predicts approximately a one-year increase in perceived age. Participants who identified themselves as black only perceived names as 2.9 years younger than did participants who identified themselves as white only ($p < 0.001$). Furthermore, all else being equal, men participants perceived names as on average 1.5 years younger than women participants did. There was no significant predicted association between the highest degree a respondent earned, nor whether the respondent was born in the United States or abroad, and the perceived age of the name (although the latter may be due to the small number of participants born outside of the United States). The model overall explained only a very small amount of variance in perceived age ($R^2 = 0.03$), suggesting that although respondent demographics are related to age perception, they have a relatively weak predicted effect. Nevertheless, these results suggest that researchers should be cautious about generalizing expected name perceptions to all survey samples, particularly when their sample is skewed older or younger than their population of interest.

Table 3: Ordinary least squares regression predicting the age perception of a name by respondent characteristics (name × respondent level)

	(1)
Chronological age	0.228†
	(0.024)
Gender (ref = woman)	
Man	−1.502†
	(0.496)
Race (ref = white only)	
Black only	−2.921†
	(0.838)
Other	0.044
	(0.704)
Degree (ref = did not finish high school)	
High school	−0.445
	(1.442)
Junior college	−1.140
	(1.462)
Bachelor	−1.115
	(1.402)
Graduate	−0.679
	(1.465)
Nativity (ref = foreign born)	
U.S. born	1.679
	(0.931)
Constant	29.067†
	(1.865)
R^2	0.030

Sample includes 7,829 name perceptions (respondents by name perception) completed by 830 respondents. Standard errors in parentheses. Standard errors are clustered at the respondent level. † $p < 0.01$; ∗ $p < 0.05$.

Comparing Perceptions with Real-World Naming Patterns

The expected year of birth based on real-world naming patterns differed significantly from perceptions of age for many of the names in my sample. In particular, I compared the perceived chronological age of a name (based on the novel data collection in this study) with the average birth year (based on Social Security Administration data) for babies given that name (as a measure of the true expected birth year of a randomly selected American, dead or alive, with a given name). I call this difference an "error" in perception, in the sense that it captures the extent to which people's perceptions of the age of a name may not match with a researcher's guess at age signaling based on birth record data.

Some names, like Deloris, Everly, Debra, and Beckett, were perceived as up to 36 years older than their true population means (birth years 1990, 2015, 1998, and 2013, respectively). Other names, such as Deja, Perlie, Booker, and Purlie, were perceived as up to 55 years younger than their true population mean (birth years 1940, 1924, 1940, and 1928, respectively). Although the difference between perception and average birth year overall correlates with the average birth year (corr $= 0.92$, $p < 0.001$), the relative recency of name's popularity does not entirely explain the discrepancy in perception. Model 1 in Table 4 shows results from a regression predicting the difference between average perceived chronological age and the SSA-based average age (2020 minus average birth year). Overall, the ages of

truly older names were often underestimated: higher true average population age ("SSA age") predicted a lower-than-accurate perceived chronological age (one year older age predicting a 0.7 year younger-than-accurate perceived age). Furthermore, all else being equal, names that have been popular over a longer period of time ("true age generality" in Table 4, i.e., names that have a higher standard deviation in birth year) were more likely to be perceived as younger than birth records would suggest. Names that had a higher spread in their perceived chronological age were predicted to have an older-than-expected perceived chronological age, suggesting that when there is more uncertainty about the age of a name, people may overestimate ages. The relative popularity, racial perceptions, and gender perceptions did not significantly predict error in age perception. However, names that were reported as more likely to have parents who did not finish college were predicted to have lower-than-expected chronological age perception. Note that, all together, this model explains a very high amount of the variance in the difference between average perceived chronological age and true population age ($R^2 = 0.92$). These results indicate that truly older names, names that have been popular over a longer period of time, and names that were perceived as lower class tend to be perceived as younger than expected, and names that were more age-ambiguous were likely to be perceived as older than expected.

Model 2 in Table 4 shows a similar model that, rather than predicting the raw difference in average perceived age and the true population average, used the absolute value of that difference as its outcome. This model can therefore be interpreted as predicting the magnitude of error in age perception, regardless of the direction of that error.[8] Here, truly older names had higher predicted error in perception; one year in true age predicts a 0.24-year larger error in perception. Low popularity names were also associated with higher-error names; compared with the middle 50th percentile in popularity, low-popularity names were predicted to have a 3.3-year error in chronological age perception. Gender, race, and parental education perceptions were not associated with the magnitude of the error. These results indicate that truly older names and low-popularity names are associated with age perceptions that differ from what would be expected from looking at birth records.

Deriving Candidate Names for Researchers

These results suggest that names signal many features of a person, and when researchers use names in vignettes in data collection, they should be cognizant of how the name they choose may signal age in addition to gender and race. They also suggest that researchers interested in intentionally signaling age can do so through name selection. Based on the average age, gender, and race perceptions in my data, Table 5 lists names that are most likely to signal particular combinations of age, race, and gender. Each cell represents the top five white- or black-signaling names that also strongly signal gender (greater than two-point difference in likelihood of being a woman vs. a man) and whose average perceived chronological age is within the decade indicated. These names may be useful for researchers creating vignettes about fictional people who vary across these categories; however, because

Table 4: Ordinary least squares regression predicting perception "error": the difference between perceived age and expected real-world age from birth records

	Model 1	Model 2
SSA age (2020 minus average birth year)	−0.700†	0.242†
	(0.021)	(0.028)
Lack of specificity of perceived age (standard deviation in perceived chronological age)	0.706†	0.731†
	(0.103)	(0.136)
True age generality (standard deviation in SSA average birth year)	−0.123*	−0.092
	(0.051)	(0.067)
Popularity of name (SSA) (ref = middle 50th percentile of 228-name sample)		
Low popularity (bottom 25 percentile)	−0.257	3.265*
	(0.986)	(1.309)
High popularity (top 25th percentile)	0.897	1.944
	(1.049)	(1.393)
Perceived gender (average relative likelihood that person is a woman compared with a man—each on five-point scale)	−0.204	−0.082
	(0.128)	(0.170)
Perceived race (average relative likelihood that person is white compared with black—each on five-point scale)	0.059	−0.073
	(0.347)	(0.461)
Perceived parental education (average relative likelihood that parent of person with name did not go to college compared with likelihood they did go to college—each on five-point scale)	−2.818*	−0.129
	(1.152)	(1.529)
Constant	15.882†	−5.850†
	(1.223)	(1.623)
R^2	0.888	0.525

Model 1 is perceived chronological age minus average SSA age. Model 2 is the absolute value of perceived chronological age minus average SSA age. Standard errors in parentheses. Each model contains 228 observations (names). † $p < 0.01$; * $p < 0.05$.

of the possibility of interactions with additional information in a vignette, I recommend pretesting newly designed vignettes to check that they indeed signal the demographics intended.

Note that in this table, there are very few names that signal older ages and blackness. This lack of older black names fits with the observed association between perceived age and likelihood of a name being white compared with black (see Figure 1(b) and Table 2) and suggests that (1) researchers who wish to signal old age and blackness through a person-vignette may need to do so through additional pieces of information about the person beyond just a first name and (2) researchers who use names to signal race may need to include more explicit signals of age to avoid conflating race and age.

Discussion

The 228 names I tested in this study consistently and significantly signaled ages from 23 to 65 years. Most were highly gendered, with only a handful being seen as having relatively equal likelihoods of belonging to a woman and a man. Replicating past research, names were also highly racialized; some names were seen as having very

Table 5: Top five names that signal combined age, gender, and race categories

		Woman	Man
Age 20–30 years (62 names in sample)	White	Chelsey Emma Katlyn Kaitlyn Hannah	Ethan Connor Cody Logan Hunter
	Black	Tanisha Ashanti Aisha Kenya Denisha	DaQuan Jayvon DeAndre Keyshawn Devonte
Age 30–40 years (84 names in sample)	White	Molly Madeline Katie Heidi Emily	Seth Brad Brett Dustin Jake
	Black	Lakisha Latoya Ebony Latasha Shanice	Latrell Tyrone Jamal Kareem Rasheed
Age 40–50 years (52 names in sample)	White	Claire Laurie Carol Hilary Jill	Neil Peter Dudley Jack Doug
	Black	*None found in 228 names tested*	Leroy
Age 50–60 years (25 names in sample)	White	Joan Evelyn Barbara Margaret Carole	Henry Arthur Frank Walter Delbert
	Black	*None found in 228 names tested*	*None found in 228 names tested*
Age 60+ years (Five names in sample)	White	Deloris Patsy Dolores	Dick
	Black	*None found in 228 names tested*	*None found in 228 names tested*

Steps used to select names for this chart:

1. Age: Average perceived chronological age is within decade indicated.
2. Gender: Man and woman names are at least two points (out of a five-point scale) more likely to be perceived as men or as women. Gender-neutral names have on average less than one point difference in perceived likelihood of being a man or a woman.
3. Race: I show the top five race-signaling names that fit above criteria and had at least a one-point difference in likelihood of being white or black. This means that black names are names that were seen at least one point (out of five) more likely to be black than white, and white names were seen as at least one point (out of five) more likely to be white than black.

high likelihood of being black, and others were seen as having a very high likelihood of being white, with a few dozen names more racially ambiguous. Contrary to prior research, names only weakly signaled parental education. Although this may suggest that names signal class less strongly than previously thought, it may also be simply due to either (1) the way I measured perceived class through expected parental education or (2) that I did not actively select for names in my sample that

varies across class, beyond what was already captured in the names from Gaddis (2017a, 2017b).

Participants' perceptions of the age of a name interacted with their perceptions of race: names that they perceived as older were very unlikely to be perceived as more black than white. This may be due to at least three reasons. First, it is possible that such names exist but were not included in my sample of names. My main source for black names was Gaddis (2017)'s name list—it is possible the set there skewed young, given Gaddis's name selection method that focused on birth records from the early 2000s. There are very few sources describing predominantly black names from before the second half of the 20th century; although I also included the 21 names from the only source to my knowledge that describes historically black names (Cook et al. 2014), it is possible that those names, which were given to black men between 1900 and 1920, were too old and therefore unfamiliar to people. Second, it is possible that there are truly very few names that signal old age and blackness due to the post-Civil Rights Era increase in usage of predominantly black names (Fryer and Levitt 2004). However, this would not explain why the names most likely to be seen as black are on average seen as *so* young: almost all are perceived on average to be less than 35 years old (which would mean they were born around 1985, which was 20 years after the supposed beginning in rising popularity of distinctively black names). Third, it is possible that this association is due to complex interactions between perceptions of race and perceptions of age. Although my results cannot speak to mechanisms directly, it is possible that when trying to interpret a person whom a perceiver expects to have lower status in society (such as a black person), they "discount" their age and perceive the person as younger and therefore additionally lower in status (see Freeman and Ambady 2011; Kelley et al. 2017; Macrae and Bodenhausen 2000). Future research should examine the interaction between race and age perception, including the role that status may play in such person construal processes.

I also found that people's perceptions of the likely age of a person with a given name can be very different from the true expected birth year based on national birth record data. Perhaps unsurprisingly, names that have low frequency in the population and names that have not been popular for many decades are associated with greater errors in age perception. Additionally, all else being equal, names that have been popular over longer periods of time are associated with perceptions of age that are younger than the true cohort-based population. These results suggest that researchers cannot simply rely on birth record data as a perfect proxy for the age signaling of a name. If researchers are concerned about the possibility of age perception based on a name biasing results, they should pretest the perceived age of a name (or use other researchers' results on perception, such as those presented here; see the online supplement for all results) before using it in a vignette.

The fact that names systematically signal age may be particularly troubling for research methodology when an experiment is designed to test for some other type of discrimination, but by unintentionally varying the age association of names in vignettes across condition, may be unknowingly subjecting itself to confounder bias. I indeed find evidence for such potential confounding in even the most highly cited name-vignette experiments. For example, Bertrand and Mullainathan (2004) use 36

names to signal variation across four race/gender categories (black woman, black man, white woman, white man) on fictional resumes that they submitted to 1,300 job postings across a variety of industries and occupations in Boston and Chicago. They find systematic discrimination against applicants with black-signaling names: such fictional resumes received three-quarters the callback rate of resumes with white-signaling names. I included all 36 names in my data collection and find that there may also have been systematic variation in the age perception of these names: names they had classified as black (e.g., Aisha, Latoya, Darnell, and Kareem) were seen by my participants as on average significantly younger than names that the authors had classified as white (e.g., Carrie, Sarah, Brendan, and Neil; name-level $p < 0.01$). This difference is shown graphically in Figure 2. This suggests the possibility that the differences in callback rates were due not just to racial discrimination, but also to discrimination against younger-seeming applicants, or race-age-gender interactions in discrimination. In this particular case, the existence of racial discrimination in hiring (including replications using the same framework but different names) is extremely well documented, and hiring managers in the audit study had access to additional information about a person's age than just their name from the fictional resumes. However, my analysis points to the fact that researchers may be introducing unnecessary noise into their data collection when failing to account for the age signaling of names. This noise may result in overestimates of effects, or it may mask true patterns. It is therefore important for researchers to consider how the names they select signal age in order to get the most accurate possible point estimates for their outcomes of interest. In particular, researchers who use names to signal race should also explicitly signal age in order to avoid accidentally signaling age through the racialized name.

My survey experiment tested perceptions of age, gender, race, and parental education based on *only* a first name. It is likely that having additional information about a person, such as their last name, occupation, or interests, would change the perception of that person's demographics, given that these traits are also raced, gendered, aged, and classed (Crabtree and Chykina 2018; Derous and Decoster 2017; Taylor 2010). Future research should examine how person perception relies on first names *vis a vis* other information about a person and whether the age, gender, and race perceptions of a name are strong enough to impact person perception even when additional information is present.

Future research must also examine how the age signaling of names may vary over time. Given that names are cohort-specific, as cohorts age and new Americans are born and given names, the average real-world age of people with a certain name will change. This suggests that the age-related meaning of names will change as well. However, my data suggest that the change in age perception may not happen as linearly as simple population change over time may suggest: people's perceptions of age do not match well with the real-world expected age of a particular name. This suggests that researchers should not only not rely on birth record data as a proxy for age perception, but they also should not take perception data (such as those from this study) for granted decades after the data have been collected. Researchers interested in using names in their vignettes should be wary of using dated information on the age signaling of names in their population of interest.

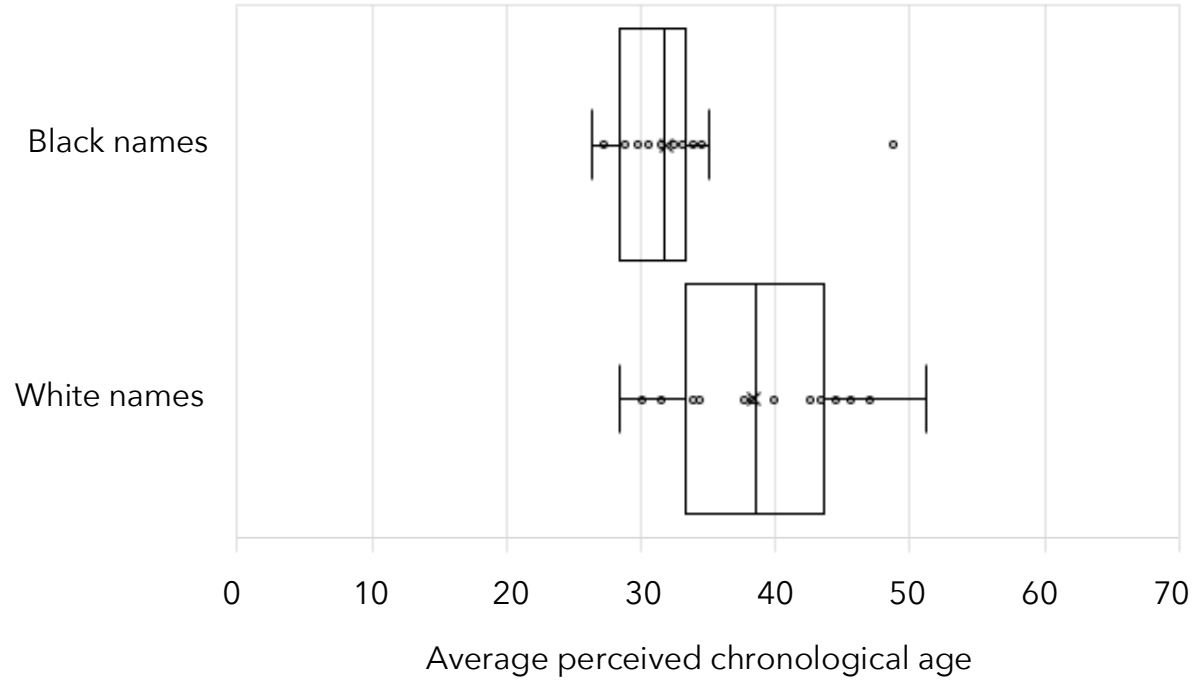

Figure 2: Average age perceptions of the 36 names used in Bertrand and Mullainathan (2004). The difference between means is significant at $p < 0.01$ (measured at the name level; $n = 36$).

This research confirms that names signal age in addition to gender and race. This result raises the question: why use names in vignettes in the first place? As described in the introductory section, there may be good reasons to use names describing fictional people—sometimes it is necessary for believability, such as in field studies where a fake resume is sent out to real-world employers, and sometimes it may aid in creating the cognitive conditions a researcher wants to induce in participants (e.g., helping make a fictional person seem more real). However, this article shows that using names in vignettes is not without its costs—names may signal a multitude of things, including and beyond a person's demographics, that may bias or obscure results. Researchers may wish to consider whether they truly need to include a name at all in their vignette, rather than use more broad terms such as "a person" or even "Person X." Furthermore, given the likelihood that last names are weak signals of age, it is possible that using simply last names, rather than first names or first and last names, could be a way to avoid signaling age entirely while still signaling race and region (Crabtree and Chykina 2018; Gaddis 2017a, 2017b). Future research could consider this and other ways to signal age-neutral hypothetical people in vignettes and stimuli.

In order to study person perception, I asked participants directly what age, as well as what gender, race, and class categories, they thought an average person with a given name was likely to be. This operationalization is simple and matches with the current standard way to measure such name perception (e.g., Gaddis 2017a, 2017b). However, it only captures one dimension of perception: the conscious

category membership that a respondent is able to consider and report. It is possible that although participants consciously report perceiving names to be a certain age (or gender, race, or class), their true person construal based on a name is much more complex. For example, past research has shown that even beyond gender category membership, names are associated with varying degrees of masculinity and femininity in ways that impact behavior, such as the way that a teacher treats a student (Harris 1977). It is similarly possible that age perception, and therefore participant behavior, may operate through more than just a single conscious expected chronological age. Research on how names signal meaning, and therefore can alter participant behavior when used in research, is a nascent field. Future work should continue to examine category signaling of names beyond just conscious reporting, including through how different names may trigger certain stereotypes, or how the way a name is presented (e.g., first name vs. full name, how the vignette is worded, etc.) may further impact the way a respondent makes sense of what the researcher is attempting to communicate and how they respond accordingly.

In sum, I have shown that names signal age in systematic ways that are not always well matched with true population variation in the average birth years of names. Researchers who use names in vignettes in their data collection must be cognizant of the way and extent to which the names they select may signal an age of the hypothetical person, and therefore potentially change participant behavior and thus reduce the generalizability of results.

Notes

1 Although researchers assume names signal gender, there is surprisingly little research directly testing this, particularly compared with the amount of research on race signaling. Names are generally assumed to be highly gendered; this assumption may be reasonable, given research on the gender patterning and meaning in first names across cultures (Alford 1987; Lieberson et al. 2000). However, my own analysis of national birth records shows that even highly gendered names are given to the other sex category, and research on androgynous names show that some names are weakly associated with gender category across the population (Lieberson et al. 2000). As I will describe later, I test gender perception explicitly.

2 SSA data prior to 1940 are estimated. The SSA data provide rates based on name by sex, such that for many names there are two observations per year (the number of male and female babies born with that name). For all my analyses of SSA data presented in this article, I collapsed across male and female babies in order to get a fuller picture about the popularity of names over time. I then test perceptions of gender in addition to perceptions of age, race, and class.

3 One additional name, "Ann," was unintentionally included due to an error in transcribing "Anne." However, I keep both names in the sample given their potential utility to researchers.

4 An exception to this expectation may be due to associations between age and ethnicity. Because of shifts in immigration flows from Europe early in the 20th century to Asia and Latin America in the last 50 years, as well as differential fertility rates by ethnic groups in the United States (see Lee and Bean 2004), some names that signal Asian or Latinx ethnic category membership could be more present in younger Americans than names

that signal specific European ethnicities. Future research must therefore examine the age-signaling power of last names as well as first names.

5 Names were tested in two different survey waves. Two hundred one names were tested March 19 to 21, 2020. Twenty-seven additional names, plus one unintentional duplicate name from the first wave, were tested April 24 to 25, 2020. I did not allow respondents who had participated in the first wave to participate the second wave, and therefore I treat these two waves together as a single randomized experiment. Which wave the name was tested in is reflected in the online supplement.

6 All results are similar if I use the ratio between perceived likelihood of groups, rather than the difference.

7 Table 1 and Table 2 both predict the perceived chronological age of a name, but at different levels (name level vs. observation level). As a robustness check, I also ran a multilevel model predicting perceived age clustered at the name level; all patterns were identical in sign and significance.

8 As a robustness check, I also implemented this model as a gamma regression (given the nonnegative outcome) and found equivalent trends.

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