Identification in Interaction: Racial Mirroring between Interviewers and Respondents*

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Abstract

Previous research has established that people shift their identities situationally and may come to subconsciously mirror one another. We explore this phenomenon among survey interviewers in the 2004-2018 General Social Survey by drawing on repeated measures of racial identification collected after each interview. We find not only that interviewers self-identify differently over time but also that their response changes cannot be fully explained by several measurement-error related expectations, either random or systematic. Rather, interviewers are significantly more likely to identify their race in ways that align with respondents' reports. The potential for affiliative identification, even if subconscious, has a range of implications for understanding race-of-interviewer effects, the social construction of homophily, and for how we consider causality in studies of race and racial inequality more broadly.

Keywords: Racial Categorization, Situational Identity, Survey Methodology

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Research demonstrates that acts of identification are profoundly influenced by social interaction and context. People often alter how they present themselves depending on the context or type of interaction (Antaki and Widdicombe 1998; Ashmore, Deaux, and McLaughlin-Volpe 2005; Bobo and Fox 2003; Renfrow 2004; Richeson and Somers 2016).[1] Racial identification, in particular, can be influenced by myriad factors and is more malleable than commonly believed (Bratter and O'Connell 2017; Harris and Sim 2002; Liebler et al. 2017; Liebler and Hou 2020; Vargas 2015). It also is well established that, when interacting, people tend to mirror each other's behavior; replicating gazes, posture, tone of speech, yawns, and more (see Ambady and Weisbuch 2010 for a review). These three lines of inquiry span subfields in sociology and psychology and are typically treated as distinct. However, their combined insights lead us to ask whether people engaged in interaction might also mirror racial identifications?

In particular, we explore how survey interviewers record their racial identification when asked to categorize themselves following each interview they conduct. Our data come from the General Social Survey (GSS), which includes repeated racial self-identifications of survey interviewers from 2004 to 2018 (Smith et al. 2018). Whereas previous research compared racial identifications collected over intervals of several months, years, or decades (e.g., Harris and Sim 2002; Liebler et al. 2017; Saperstein and Penner 2012), our data include race reports over months, weeks, days, and even within the same day. These data allow us to explore whether or not an interviewer's racial identification varies in patterned ways along with interactional or contextual factors that vary across interviews.

[1] Our focus is on identification, or the act of identifying oneself to others. However, we draw on literature on identity, broadly construed, in part because conceptual distinctions between the public and private facets of identity are not always made clear (see Brubaker and Cooper 2000).

Our analysis reveals that interviewers are significantly more likely to align their racial self-identification with the respondent's own identification than would be expected due to chance. This reporting alignment cannot be fully explained by either random measurement error or several plausible hypotheses related to systematic error. Rather, the observed patterns of fluidity are more consistent with our hypothesized process of racial mirroring. Most of the observations in our data represent stable racial identification, as would be expected given the long history and institutionalization of race and racial classification in the United States. Nevertheless, the potential for mirroring in identification, whether conscious or not, has implications for how we conceptualize race and racial identification, how those concepts are applied in survey research and design, and how researchers explain racial inequality – including processes of homophily – more generally.

RACIAL IDENTIFICATION IN TIME AND CONTEXT

Although most social scientists see race as socially constructed and not biologically or genetically determined (e.g. ASA 2003), most social science research continues to treat race as a fixed individual characteristic, leaving changes in racial identification relatively understudied. Over the past two decades, as access to longitudinal data has increased, a body of work has grown about the levels, correlates, and consequences of racial fluidity, in the United States and beyond.

Typically, researchers in this area highlight changes in racial identification that occur over time or as context changes (Roth 2016). Over time, individuals can come to understand and/or present themselves differently, changing how they self-identify and how others classify them (Liebler et al. 2017; Saperstein and Penner 2012). This may occur, in part, because cultural conceptions of race change (Loveman and Muniz 2007; Loveman 2014), people's self-conceptions change (Jiménez 2010), and/or the available response options change (Chang 1999; Loveman, Muniz, and Bailey 2012). Apart from changes over time, shifting contexts can change how individuals see themselves or others (Roth 2012). For example, adolescents may identify differently if asked about their race at school or at home (Harris and Sim 2002), individuals may align their presentation of self with their goals and expectations (Renfrow 2004), and the same people can be perceived differently depending on their surroundings (Freeman et al. 2015).

We suggest that it is also useful to explore how racial identification shifts across interactions. We distinguish between racial categorization in 'interactions' and across 'contexts': the former refers to instances of racial categorization in particular moments while engaging with particular individuals and the latter refers to changes in categorization across the different social locations that structure those interactions. From this perspective, most prior research has addressed how changes in racial identification relate to changes in context. A change in interaction, on the other hand, refers to a new interpersonal encounter in which an individual could be called upon to identify or perform their race. Although our focus is primarily on micro-level interaction, it is important to acknowledge that these interactions occur within broader dynamics of structural racism (Bailey et al. 2017; Bonilla-Silva 2010; Sewell 2016) and shifting racial boundaries and hierarchies (Omi and Winant 1994; Wimmer 2012). Here we seek to contribute to existing work on racial formation, negotiation, and boundary crossing at the macro and meso levels (see Saperstein, Penner and Light 2013 for a review) by highlighting parallel processes occurring at the interactional level.

RACIAL IDENTIFICATION IN INTERACTION

To help us understand how a person's racial identification might change from one interaction to the next, we draw on the broad traditions of social interactionism (Blumer 1969), social psychological work on collective identity (Ashmore et al. 2005; Day 1998), theories of situational ethnicity (Okamura 1981), and schematic cognition (Brubaker, Loveman, and Stamatov 2004; DiMaggio 1997). What unites these perspectives is an emphasis on how individuals come to negotiate shared meanings. As Ridgeway (2009:147) put it, "We need a shared way of categorizing and defining 'who' self and other are in the situation so that we can anticipate how each of us is likely to act and coordinate our actions accordingly." These perspectives suggest that racial and ethnic categories are rooted in cultural schemas, and not inherent characteristics of individuals (Roth 2012). Conceptualizing racial and ethnic categories as schemas suggests a process of simplification whereby individuals recognize an instance of a given category and use their schematic knowledge to fill in relevant details to guide future perception (DiMaggio 1997). Racial schemas are the negotiated meanings that individuals can deploy (or not) and ascribe to others (or resist ascription) depending on their salience in a given interaction (Day 1998).

Our case, a survey interview, is an instance where individuals are likely to interactionally negotiate their identities. For example, if the interviewer is surprised by the respondent's racial self-identification, their frame of reference for which schema is at play might shift (Sewell 1992). Alternatively, deploying the same racial schema may have different effects in different interactions (Sewell 1992: 18). Through subtle and perhaps subconscious negotiation, interviewers and respondents may align their schematic understandings of race, including who falls into or out of a given category, what those categories represent, and the acceptable criteria for membership (cf. Morning 2018).

Individuals, however, do not reinvent the concept of 'race' in each interaction. Instead, we can think of conversation participants as belonging to a racial interactional order that imposes structure and constraints on their exchange (Goffman 1983). General guidelines can be followed so that conversations need not redefine all shared categories and references for each interaction (cf. Okamura 1981). The negotiation of shared meaning happens against a backdrop of extensive cultural repertoires that simplify the identification process (Stets 2006), including the routinization of declaring one's race on various forms. We might expect, then, that the schemas interviewers and respondents use to identify themselves and others remain relatively stable over time, but occasionally shift at the margins to accommodate unique aspects of an interaction.

Previous research on racial identification emphasizes that fluidity is not equally likely across individuals. Studies in the contemporary United States find that changes in racial identification are more common among people who ever identify as Hispanic (e.g., Brown, Hitlin, and Elder 2006), American Indian or Alaskan Native (Cheng and Powell 2011; del Pinal and Schmidley 2005), Pacific Islander (Liebler et al. 2017) or multiracial (e.g., Doyle and Kao 2007), and less common among people who initially identify as monoracial White or Black. Inconsistency between how one identifies and how one is perceived is also unequally distributed across groups. Self-identified American Indians and people with multiracial ancestry are the most likely to experience this type of "racial contestation," while self-identified monoracial White and Black Americans are the least likely, with Asian and Latina/o Americans falling in between (Campbell and Troyer 2007; Vargas and Kingsbury 2016). However, to date such research has focused on the frequency and correlates of racial identification among survey respondents. Our data include information about both interviewers and respondents, making it uniquely suited to explore interactional aspects of racial identification.

SURVEY INTERVIEWS AS AFFILIATIVE INTERACTIONS

When individuals attempt to build rapport in an affiliative interaction, they can start to exhibit mirroring behaviors. This mirroring can take several forms, from the explicit, such as highlighting shared tastes and preferences ("I like that band too!"), to the implicit, as with the tendency to mirror non-verbal behavior such as posture, accents, vocal tone, gaze, and yawns (Ambady and Weisbuch 2010). These processes appear to be fundamental to human behavior, as research suggests that observing others can cause sympathetic brain activity. For example, seeing someone express pain may cause pain-like brain activation in ourselves (Botvinick et al. 2005).

Thus, we expect interviewers who intend to build rapport may come to mirror respondents, whether they are aware of it or not. Interviewer trainings often focus on building rapport with respondents to increase response rates and the likelihood that a respondent will answer sensitive personal questions (Crano, Brewer, and Lac 2014; Sun, Conrad, and Kreuter 2021). Previous research using recorded telephone interviews and conversation analysis finds that interviewers employ a variety of observable behaviors to keep respondents engaged, from acknowledging responses and assisting with difficult questions to initiating or reciprocating laughter (e.g., Garbarski, Schaeffer, and Dykema 2016). Such studies demonstrate that survey interviews are "collaborative achievements" (see also Maynard et al. 2002) but have yet to explore how the interactional context could influence racial identification.

Assuming that interviewers are prone to subtle mirroring behaviors through their attempt to build rapport, we might expect to observe mirroring of the respondent in racial identification for several reasons. First, race will be made salient for both the interviewer and respondent throughout the interaction whenever the topic arises on the questionnaire.[2] Second, in the GSS, both

[2] The GSS includes many racial-attitude items but some have skip patterns that depend on answers to previous questions and not all questions appear on all ballots; thus all respondents are not asked all items.

interviewers and respondents are asked to identify their race and Hispanic origin.[3] The interviewer does so in private, after the interview is completed; thus, in this case, they likely are not consciously signaling affiliation with the respondent. We explore the dyadic patterns of race reporting in our data to examine whether any such identification mirroring occurs, unintentional or otherwise. When the racial identification of survey interviewers changes over time, we consider whether such changes yield more (or less) alignment between respondent and interviewer identifications than would be expected by chance.

DATA AND METHODS

The GSS is a nationally representative sample of U.S. adults living in households, which has been fielded by NORC since 1972. We use pooled cross-sectional samples from 2004-2018.[4] These data are uniquely suited for our purposes because – although racial identification is often asked at a single point in time and assumed to be constant thereafter – GSS interviewers self-identify their race and origin following each interview. Beginning in 2004, GSS interviewers recorded this information along with other aspects of the interview context (e.g., if the respondent's spouse was present and the type of structure the respondent lives in) in the interviewer remarks section, which must be completed before they can begin the next interview. By focusing our analysis on the interviewers, we can track changes in racial identification as they engage in interactions with different respondents.[5] We focus on race and origin because they are the only

[3] We refer to 'Hispanic origin' throughout to signal it is a response to a separate survey question, though a conceptual distinction between either race and ethnicity or "origin," following U.S. Census Bureau terminology, likely is not recognized by most respondents (e.g., Lopez, Gonzalez-Barrera, and Arditi 2021).

[4] We begin in 2004 because that is when the GSS first provided interviewer characteristics in public-use data.

[5] GSS interviewers are generally assigned to respondents who live nearby – roughly within a 50-

interviewer characteristics collected repeatedly after each interview, not because we expect mirroring behavior to be specific to racial identification.

We can explore variation in identification within interviewers, and not just across the interviewer pool, because each interviewer-year is assigned a unique identification number. However, because the GSS assigns new identification numbers each year, we are limited to looking at changes within interviewer-year units as we cannot track interviewers across survey years.[6] For example, if the same interviewer worked in 2004 and 2006, she would be recorded as two different interviewers in our data, and we explore how she identified herself within 2004 and within 2006 separately. Within a given year, GSS interviewers conducted an average of 17 interviews, ranging from as few as one to as many as 120 interviews, providing 20,845 reports from 1,262 interviewer-years.[7]

Interviewer Racial Identification

After completing the respondent's portion of the questionnaire and answering a series of questions about the interview context, interviewers are asked to record their Hispanic origin and racial identification. The two-question format is similar to the one used in the U.S. Census and first asks interviewers to report their Hispanic origin ("Interviewer, are you Spanish, Hispanic, or Latino/Latina? Which group are you from: Mexican, Mexican American, Chicano/Chicana, Puerto Rican, Cuban, Other. Please specify other"). Interviewers were then asked, "What is your race?

mile radius, in non-rural areas; interviewers and respondents are not explicitly matched by race.

[6] Our unit of analysis is an interviewer-year, and we maintain this specificity when describing our data and empirical findings, but we refer to "interviews" or "interviewers" for the sake of exposition when interpreting our results and discussing their implications.

[7] Across years, the number of interviewers ranged from 134 in 2016 to 194 in 2012, with an average of 158. The average number of racial reports is 17 per year, ranging from 10 in 2012 to 25 in 2016.

Indicate one or more races that you consider yourself to be," with the response options: White, Black or African-American, American Indian or Alaska Native, Asian Indian, Chinese, Filipino, Japanese, Korean, Vietnamese, Other Asian, Native Hawaiian, Guamanian or Chamorro, Samoan, Other Pacific Islander, and Some other Race. Except for the initial prompt that makes it clear the interviewer should answer about themselves, the wordings are identical to the questions asked of GSS respondents and, as with the respondents, interviewers could record up to three race responses.[8]

Although Hispanic origins are intended to be recorded separately in this format, some respondents and interviewers did report their race as Some Other Race and specified Hispanic (5% and 1%, respectively). Among people who identified as having either a Hispanic origin or race, it was most common to report a Hispanic origin without also reporting a Hispanic race (63% of respondents and 84% of interviewers responses), and least common to identify one's race as Hispanic but not report a Hispanic origin (0.06% of respondents and 0.05% of interviewer responses). Given these reporting patterns, we include "Hispanic" among the racial categories we investigate. Nevertheless, because of the two-question format, interviewers can have a fluid Hispanic origin identification, a fluid racial identification, both, or neither.[9]

Timelines of race and origin responses for three illustrative interviewer-years can be found in Figure 1. The examples are intended to show the range of variation in the data, including interviewer-years that had both stable and fluid Hispanic origins and race responses. Figure 1 also shows responses that switched from a single race to multiple, or between two different single race

[8] An example of the interviewer remarks form can be found at: http://gss.norc.org/documents/quex/2008%20REMARKS.pdf (retrieved 29 December 2020).

[9] When relevant for methodological purposes, we note when we refer to the origin question or the race question; otherwise we consider people who report Hispanic origins or identify their race as Hispanic as part of a shared Hispanic category.

responses. We opted to measure racial identification by treating any given combination of categories as distinct (i.e., monoracial White is distinct from White and Black, or White, Black, and American Indian), but our conclusions are not dependent on this coding decision.[10]

The first example in Figure 1, interviewer number 137 in 2006, conducted five interviews in total. In three of the interviews (March 11th, 19th, and 25th) the interviewer identified as Black with non-Hispanic origins. On two occasions (March 22nd and April 24th) the interviewer identified as both Black and American Indian with non-Hispanic origins. For this interviewer-year, we consider Hispanic origin to be 'stable' because the interviewer reported the same origin in each interview, and we consider the racial identification to be 'fluid' because the interviewer reported different race categories at different times. Our second example, interviewer 18 in 2006, also had a stable non-Hispanic origin and was racially fluid, identifying as White on March 18th and 23rd, but identifying as Black for the remaining 14 interviews. Lastly, interviewer 138 in 2006, exemplifies someone whose race reporting remained stable throughout the entire year, but whose origin identification was fluid. On June 10th and 20th, the interviewer recorded their origin as non-Hispanic, but for the rest of the year they identified as having a Hispanic origin (specifically Mexican or Chicano/a). The variation exemplified by these three cases provides the foundation for our analyses below.

[Figure 1 here]

In addition to the interviewer reporting their race and origin following each interview, the GSS provides a static classification for each interviewer-year based on NORC personnel files,

[10] Appendix C presents model results using two alternate codings: 1) including racial identifications as a given category alone or in combination with other categories and 2) using only the first race response.

hereafter referred to as HR files.[11] Like the post-interview responses, the HR file information is self-reported by the interviewer – on a separate form after they have been hired at NORC. This record combines race and origin and provides a different set of categories from those available in each survey interview (the HR question categories are limited to: White; Black; Hispanic; Asian; Two or more races; and No answer). Thus, responses in the HR file do not necessarily match the post-interview responses, even for interviewers with stable race and origin identification.

Descriptive statistics for the 1,262 interviewer-years can be found in Table 1, which presents the distribution of categories reported in HR forms separately for the sample of interviewer-years with at least one change in racial identification (labeled "Fluid Self-id"), and for the sample of interviewer-years with no such change (labeled "Stable Self-id"). As expected based on previous research (e.g. Liebler et al. 2017), interviewers recorded as White in their HR form are least likely to have fluid racial identification in a given year (14 percent), followed by interviewers recorded as "Two or More Races" (28%), Hispanic (31%), Black (33%), and Asian (50%). Importantly, though, fluid responses are not limited to a subset of interviewers who do not have a preferred category available to them, such as interviewers who are primarily recorded as Hispanic or multiracial in their HR file.[12] Further, men and women interviewers are approximately equally likely to have a fluid racial identification, and interviewer-years with stable and fluid racial

[11] Other information recorded in the interviewer's HR file include sex, age, and years of NORC experience. Eighty one percent of interviewers were female, the average interviewer was 53 years old, and the average interviewer had worked at NORC for 3.3 years.

[12] Although we explore fluidity for multiracial interviewer-years as reported in their HR record, it is important to note that one could operationalize a multiracial interviewer in several ways with these data. An interviewer could have two or more races reported on their HR form, could identify as two or more races following any interview, could identify as different single races at various times following interviews, or identify using a category that differs from the HR report. We do not claim that an HR report of multiple races is the definitive measure.

identification tend to be of comparable age, NORC tenure, and GSS interview caseload.[13] This suggests fluid racial identification is a phenomenon experienced by a wide range of interviewers.

Finally, we cross-tabulate interviewer-years with either stable or fluid post-survey racial identification and either stable or fluid Hispanic origin identification (Table 1). There is some overlap between these categories, but there are 3.9 times as many interviewer-years that exhibit fluidity on one dimension or the other compared to both. Thus, interviewers experience fluidity in both their Hispanic origin and racial identification, but these changes need not occur simultaneously.

[Table 1 here]

Analytic Approach

Our analysis proceeds in several steps. Once we establish the overall level of fluidity in the sample, we then explore the timing of changes under the assumption that rapid changes (e.g., within the same day) more plausibly suggest interaction-specific influences on identification, whereas changes that occur further apart in time or in patterned ways across a survey year can be better explained by other processes that are not interaction specific. Next, we explore the relationship between respondent and interviewer identification, including whether observed matches can be explained by random or systematic measurement error. Lastly, we turn to fixed effects regression analyses to explore whether or not aspects of the interview interaction influence how interviewers racially identify.[14]

We start our assessment of measurement error with a randomization test to assess whether

[13] For interviewer descriptive statistics by each survey year and a comparison of the full tenure distributions for fluid and stable interviewer-years, see Appendix A.

[14] Vaisey and Miles (2017) discuss the limitations of fixed effects regressions for causal interpretation. See Appendix B for a discussion of why their critiques are not an overriding concern in our case.

respondents and interviewers match more often than would be expected if their identifications were independent. If there is random measurement error in the racial identification of interviewers, the order in which they interview respondents shouldn't matter for the interviewer's racial identification – instead you could think of the interviewer as having a list of possible racial identifications that they select randomly from following each interview which may or may not randomly match the respondent's identification. By comparing the amount of matching between interviewers and respondents to the amount of matching we observe when we randomize respondent order, we can see if the observed interviewer racial identification is consistent with this random measurement error explanation, or if, on the other hand, the observed matching between interviewers and respondents appears non-random. Next, we consider cases where interviewers exactly match all of the respondent's identifications because these could also represent confused interviewers who thought they were supposed to identify the respondent's race rather than their own. Specifically, we adjust our randomization test to exclude all exact matches between interviewer and respondent and instead determine whether *aligned* responses (i.e. when interviewers and respondents match on at least one but not all identifications) are more common than would be expected by chance.

To help visualize the observed response patterns, we also report an illustrative cross-tabulation of interviewer and respondent racial identifications among interviewers who tend to identify as mono-racial White (i.e., they select White alone more than 65% of the time).[15] We then fit a Poisson regression model to the cross-tabulation to estimate the relative frequency that interviewers report a non-White race that exactly matches the respondent (i.e., reporting Black

[15] For a comparison of rates of fluidity among interviewer-years by their most commonly identified race categories, see Appendix A.

alone when the respondent does the same), and the frequency of interviewers reporting a non-White race that is aligned with the respondent (i.e., reporting White and Black when the respondent identifies as Black alone). The model includes covariates for the rows and columns (to control for overall reporting tendencies), a dummy variable identifying cells with an exact match, and a dummy variable identifying cells with an aligned response.[16] Characteristics of the interviewer, such as their years of experience or their HR racial identification, represent alternative systematic measurement-error related explanations for the observed changes (cf. Alba, Lindeman, and Insolera 2016; Kramer, DeFina and Hannon 2016); see Table 1 for evidence that these characteristics cannot fully account for the level or patterns of fluidity in these data.

Finally, we model the interviewer's racial identification as a function of characteristics of both the respondent and the interviewer while controlling for interviewer-year fixed effects to account for stable interviewer characteristics. If some interviewers are more or less likely to make recording errors, are assigned to particular areas, are differently specialized across the NORC interviewer pool, were trained differently across years, or are predisposed to a particular race response, as long as those characteristics are fixed for a given interviewer-year they cannot drive our results. The use of interviewer-year fixed effects means that these models exclude variation

[16] Specifically:

$$Y_{ij} = Pois(\lambda_{ij})$$

$$\lambda_{ij} = e^{\beta_0 + \beta_i + \beta_j + \beta_e exact_{ij} + \beta_a align_{ij}}$$

Where Y_{ij} is the observed count row i and column j, and $exact_{ij}$ and $align_{ij}$ are indicators for cell ij as defined above. Because the cross-tabulation of all interviewer and respondent self-identifications is relatively sparse, we compare the predicted number of zeros to the number of observed zeros to assess zero inflation. The predicted number is 5,251, while the observed number is 5,224, suggesting that zero inflation is not an issue for this model. We also test the dispersion assumptions of the Poisson model and find that the dispersion ratio is 0.998 and statistically indistinguishable from 1. Indeed, a negative binomial model fails to converge.

between interviewer-years and instead only identify differences *within* interviewer-years. [17] Thus, the models do not predict which interviewers are more likely to identify as White overall, they predict under what circumstances in a given year the interviewer is more likely to self-identify as White. Interviewer-year fixed effects are more conservative than interviewer fixed effects would be, as they are equivalent to the interaction between interviewer and year fixed effects.

These models address concerns about some scenarios of random measurement error in reporting as well. If the observed response change is the product of random measurement error then periods of fluidity would be randomly distributed over time and should be independent of other variation after controlling for interviewer-year fixed effects.[18] Although substantial random measurement error could introduce instability in our coefficients, it would not introduce consistent estimation bias.[19] In each model, standard errors are clustered by interviewer-year to account for correlations among responses within interviewer-years.

We estimate separate linear probability models predicting the interviewer's racial identification for all monoracial categories that have sufficiently large sample sizes in the GSS: White, Black, Asian Indian, Chinese, Some Other Race alone, and Hispanic, whether reported on

[17] Because we cannot identify interviewers across survey years, our results could be influenced by anomalous repeat interviewers who show up in the data as separate interviewer-years. However, we examine differences by interviewer tenure and see similar patterns among interviewers who have short and long tenures with NORC (see Appendix A and C). Thus, though more experienced interviewers will be overrepresented in our data, in some sense, this does not appear to be driving our results.

[18] Not including interviewer-year fixed effects could yield false positives under a random measurement-error model if interviewer characteristics were correlated with interviewer's race. Specifically, our models control for a fixed propensity for interviewers to 'misreport' their race within interviewer-years. This would suggest that fluid interviewer-years reflect a different kind of interviewer. For further discussion, see Saperstein and Penner (2016).

[19] We conclude that our results are not the spurious result of a single unstable estimate because the results are similar across racial classifications and for various sub-groups.

the origin question or by writing in a Hispanic racial identification.[20] These outcomes are binary, with the category of interest compared to all other possible responses; nevertheless, we argue linear probability models are preferable to logistic regression models for several reasons. First, because we incorporate interviewer-year fixed effects, logistic regressions are only estimable conditional on interviewers experiencing a change in the dependent variable in a given year whereas linear probability models can incorporate information from all interviewer-years. Second, because we are interested in the marginal effects on racial identification and not in predicting the identification of interviewers, we are less concerned about the possibility of out of bounds prediction.[21]

All models include controls for the logged population size of the place of interview, whether the interview was conducted in Spanish, and whether or not the interviewer reported a Hispanic origin following the interview. We also account for characteristics of the respondent beyond their self-reported race and origin, including whether or not the respondent had ever been married, their age, and their interviewer-recorded sex category (female/male).

Limitations

Though we treat our data and apply our methods as carefully as possible, no study is without limitation. First, we expect our results to generalize beyond these interviewers or this particular survey setting, as we address in the discussion, but we cannot make strong generalization claims based on a convenience sample of interviewers (as opposed to the probability sample of

[20] Results are similar when either Hispanic origin or Hispanic race identification is included alone. The Hispanic identification models do not control for Hispanic origin; all other controls are the same.

[21] Interviewer-specific probabilities of identifying as a given race tend to be very close to one or zero, and roughly half (54%) of the fitted values from regressions in Table 3 are outside the bounds [0, 1]. However, conditional logistic regression models produce coefficients in the same direction with comparable significance (see Appendix C, Table C6).

respondents). Second, if interviewers work for multiple years at NORC, we cannot follow them across years. We also cannot be sure of the order of interviews conducted by a single interviewer within the same day.[22] Finally, we acknowledge that linear probability models are also susceptible to heteroskedasticity in the error distributions and incorrectly specifying the functional form if the true relationship is non-linear, but feel these costs are small relative to the advantages for our purposes. Even with these limitations, we believe our analysis provides unique insight into how frequently and under what circumstances a person's racial identification is subject to change across interactions.

RESULTS

We find at least one change in the interviewer's self-identified race or Hispanic origin in 23 percent of interviewer-years between 2004 and 2018.[23] Such changes occur, on average, in 5 percent of GSS interviews.[24] Thus, we observe a notable amount of fluidity that is similar in magnitude to previous research on race response change, but not so much as to suggest that there are no social constraints on an individual's decision about how to identify.[25] To unpack the

[22] On average, interviewers conducted multiple interviews on 12% of the days they spent interviewing. When interviewers conducted multiple interviews on the same day, they averaged 2.1 interviews.

[23] 256 interviewer-years have at least one change in racial self-identification, and of the 1,006 with stable racial self-identification, 31 have fluid Hispanic origin self-identification, for a total of 287 interviewer-years with at least one change in race or origin out of 1,262 interviewer-years (see Table 1).

[24] We count a change in race or origin identification as consecutive differing reports. We do not observe the precise ordering of interviews within a given day, so we calculate all possible orderings to break ties and take the average. See Table 2.

[25] For comparison, Harris and Sim (2002) find 12% of youth identified inconsistently between surveys conducted several months apart, at school and then at home, Smith and Son (2011) find 8% of adults inconsistently racially identify in the 2006-2008 GSS Panel Survey, and Liebler et al. (2017) find 6.1% of their sample of both children and adults was recorded differently in the 2010 census compared to Census 2000.

variation in racial identification, we first explore whether or not fluidity is patterned by interview timing. We go on to consider several additional measurement-error-related explanations, both random and systematic, before examining whether or not the patterns of fluidity are consistent with racial mirroring between the interviewer and respondents.

Interview Timing

We start by asking whether racial identifications are more likely to differ between interviews that occur closer together or further apart in time. We do this by examining all interviews conducted by the same interviewer on the same day, consecutive interviews conducted on the same day through five days apart, on the same day through ten days apart, on the same day through fifteen days apart, on the same day through thirty days apart, and finally all pairs of interviews over the survey year (see Table 2). Table 2 shows that there is a high degree of similarity across the different time windows, ranging from 4.2% in the same day to 4.8% within a 30-day window. This relative uniformity is consistent with the idea that observed fluidity does not occur only as a product of shifts between relatively stable identities, but that the context of each interview could influence interviewers' identification.

[Table 2 here]

We also explore how fluidity is distributed across time during the survey period. To do so, we construct plots of interviewer-year, mean-centered racial identification over time and visually compare them to ideal-type plots for various scenarios. By removing the interviewer-year mean before plotting the probabilities, these charts plot differences in probabilities *within* interviewer-years (akin to interviewer-year fixed effects). Thus, the plots are unaffected by changes in the interviewer pool over time both within and between years (e.g., if the pool of interviewers becomes older or younger, or more or less educated). These plots are normalized to start at day zero – the first interview in each survey year – and allow us to explore whether there are long-term trends in the probabilities of reporting specific categories, or if particularly odd days or weeks produced anomalies in data collection.

Figure 2 shows three ideal-type plots reflecting different scenarios of interview timing on racial classification within interviewer-years. In each plot a solid line is drawn at zero and a dashed line shows the average within-interviewer-year change over time. The first scenario is a general increase over time, which would imply that individual interviewers became more likely to identify as the given category over the course of the survey period. Second, we explore the possibility that certain days of the week are more prone to certain category changes – e.g., if interviewers are more likely to select the first option (White) on Fridays – then we would expect to see a cyclical pattern in these plots.[26] Finally, if a particular day or week saw interviewers selecting a category at higher or lower levels, the points would fall far from zero, representing a spike or dip in the probability of identification. Figure 3 plots the observed interviewer-year, mean-centered probability of identifying as the four largest categories White, Black, Hispanic, and Some Other Race, which we compare to the ideal types in Figure 2.

[Figures 2 & 3 here]

Overall, the points in all four panels of Figure 3 appear to be tightly clustered around zero, with no noticeable cyclical rhythm, or particularly anomalous weeks where probabilities change dramatically. Nevertheless, several features of these graphs are worth noting. First, there are a few outliers, particularly when interviews start each year. It is possible that there is greater variation in

[26] Though we mention Fridays here, it should be noted that not all interviewers work a standard five-day week. Our approach to addressing this question does not put particular emphasis on the last day of a work week.

responses as interviewers become accustomed to asking others to racially identify and routinely identifying themselves. Second, the variance is higher for White and Black, two larger categories which also appear first and second in the list of racial responses, and the variance for all categories also appears to be higher later in the year.[27] Lastly, there is a slight upwards trajectory in the frequency of identifying as monoracial White. It is possible that multiracial White interviewers are more likely to drop their hyphenated status over the course of a survey year. These intuitions from visual inspection were confirmed by a series of regression models with fixed effects for day of the year, day of the week, weeks within the year, and general time trends. Although several estimates from these models were significant, considerably fewer reached statistical significance than would be expected at random.[28]

Chance, Error, or Alignment?

As the patterns of interviewer identification do not appear to be driven by either the timing of interviews or interviewer characteristics across the sample alone (see Table 1 and Appendix A), we turn to several explanations related to measurement error for why the interviewers' and respondents' identifications might match. We first conduct a simulation to test if matching between

[27] NORC does bring in a new pool of interviewers for the end of the survey year, but these "closers" do not have more fluid racial identifications (see Appendix D).

[28] No specific weeks were found to be significant. Among days in the year, only one significantly predicted identification as White, four significantly predicted identification as Hispanic, and four significantly predicted identification as Some Other Race. (With a 5% false positive rate, about 60 significant coefficients would be expected at random.) Of specific days in the week, only Thursday was significant (relative to Sunday as the reference), and only for Some Other Race. (Here, assuming the same false positive rate, we would expect about 1 significant coefficient at random.) Finally, coefficients for changes over time in identification as White and Other were positive, small, and significant. There is a downward trend in reporting both White and American Indian, which may partially offset the observed transition into the White category (see Appendix E).

the interviewer and respondent occurs more often than would be expected if the two reports were independent. To do so, we count how many times interviewers reported a racial category that matched any of the categories chosen by the respondent and then randomly reorder the respondents within interviewers. By randomly permuting the order of respondents within a given interview-year, the matching of interviewers and respondents in this simulated data can only occur through random chance. We then recount the matched responses in this new data. We repeat this procedure 10,000 times to generate a distribution of matching due to random chance. In the GSS data, we see 14,422 interviews with matching interviewer and respondent race reports. Of the 10,000 simulations, we find none have this many matches, corresponding to a two-tailed p-value of less than 0.001. Ninety-five percent of the iterations have between 13,981 and 14,025 matches, and the average was 14,003. These results indicate the observed amount of racial identification matching between interviewers and respondents exceeds the amount expected by chance, which supports our conclusion that variation in the GSS data was not produced by random error alone.

Beyond matching by chance, a commonly posited error-based explanation for the observed fluidity is that interviewers mistakenly believe the race and origin questions in the interviewer remarks are asking about the respondent. In this hypothetical, matching responses result from interviewers incorrectly repeating the respondent's answers rather than reporting their own identification. We offer three statistical tests that isolate exact matches and attempt to rule out that this pattern of fluidity – which could result from either systematic interviewer error or substantively meaningful response change – is driving our results.

First, we repeat our simulation but exclude exact matches and instead focus on *aligned* responses – i.e., responses where interviewers and respondents share at least one, but not all, of their racial responses. Whereas an interviewer identifying as Black after interviewing a respondent who identifies as Black could represent either mirroring or mistaken repetition of the respondent's answer, an interviewer reporting their identification as White and Black after a respondent identifies as Black does not reflect the same type of mistake. In our data, we see 1,582 interviews where interviewers aligned with respondents but do not match exactly, and of the 10,000 simulations, we find that none have as many aligned responses, corresponding to a two-tailed p-value of less than 0.001. Ninety-five percent of these iterations produced alignment counts between 1,508 and 1,536, with an average of 1,522. Thus, not only are interviewer and respondent race reports significantly more likely to match than expected at random, but interviewers are also significantly more likely to align with respondents in subtler ways.

Second, we exclude interviewer-years with even one exact match between race reports. Among this subset, we observe 1,485 aligned responses, and again run a simulation that randomly permutes the order of respondents within interviewer-years. As above, results indicate that the amount of observed racial identification alignment significantly exceeds chance (randomization test mean: 1,443; 95% interval: (1,436, 1,451); corresponding p-value for a two-tailed test: less than 0.001). Thus, even when we exclude data for all interviewers who ever plausibly mistook the interviewer racial identification question to be asking about the respondent, we still find that interviewers align their racial identification with the respondent more often than can be explained by chance.

Third, we exclude interviewer-years in which racial identification is highly variable and cross-tabulate interviewer and respondent racial identifications only for interviewer-years in which the same single race is reported more than 65% of the time.[29] We focus on interviewers who are

[29] Results from our Poisson model are similar when using any frequency cutoff between 65% and 95% (See Appendix F).

prone to identifying as monoracial White, in particular, which allows us to explore the extent of non-White response alignment absent especially fluid outliers as well as interactions between interviewers and respondents with stable but matching racial identification that arise either by chance or artifacts of the survey design. We also focus on interviewers identifying as White to maximize our sample size as the interviewer pool predominantly identifies as White (see Appendix A).[30] For legibility, Table 3 shows a reduced form of the full contingency table, with outlined cells to indicate exact non-White matches and cells that align on non-White identification among this subset of interviewers and respondents shaded gray. We then estimate a Poisson regression model on cell frequencies for the full cross-tabulation. The coefficients for exact matches (5.05, robust t-statistic 13.5) and aligned responses (2.6, robust t-statistic 6.7) are statistically significant. Thus, even amongst interviewers who usually identify as monoracial White, we observe both more non-White alignment and more non-White matching in their race reports than expected due to chance alone.

[Table 3 here]

Racial Mirroring

To build on our simulations and Poisson model, we turn to fixed effects regression to explore patterns of racial identification more broadly throughout the sample. All else equal, we find that, within a given year, interviewers are between 3 and 9 percent more likely to report a race that matches the respondent's self-identification than they are to report a non-matching category (see Table 4), and the increased probabilities are statistically significant for each category

[30] Results are similar if we instead focus on interviewers who identify as monoracial Black 65% or more of the time (See Appendix F).

examined except for 'Some Other Race'.[31] This suggests interviewers are more likely to identify as monoracial White, Black, Asian Indian, Chinese or Hispanic when the respondent also selected the same category. As shown in Table 5, these fixed-effects results are robust when we exclude any interviewer who always matches the respondent's exact racial identifications across the survey year. Together with the series of statistical tests described above, these estimates increase our confidence that observed patterns of fluidity include instances of interviewers mirroring the racial identifications of respondents and are not only the result of random chance or systematic errors such as interviewers who are mistakenly reporting the respondent's answer for themselves.

[Table 4 & 5 here]

Appendix C includes further robustness checks that vary our model specifications to ensure our results are not anomalous. Table C1 reports results from models that predict any identification with the given category, as opposed to monoracial identification. Table C2 reports results from models that use only the first identification of both interviewers and respondent. Table C3 varies the subset of interviewer-years included in the model, first excluding interviewers who are coded as Hispanic on the NORC HR form, then excluding interviewers who are recorded as two or more races on the HR form, then including only interviewers with a short tenure (3 years or less) or a long tenure (more than 3 years). Table C4 subsets the analyses to two-year windows to examine changes during the 14-year period. Table C5 compares estimates between cooperative and hostile respondents, respondents with good and poor comprehension, and short and long interviews. Table C6 estimates the models using conditional logistic regression. In each case, our conclusion that interviewers are more likely to report identifications that mirror respondent identifications remains the same.

[31] For linear probability models, coefficients can be interpreted directly as changes in probability.

DISCUSSION

This paper demonstrates that an individual's racial identification can change as they engage in interactions with different people. Drawing on a tradition of research that suggests the salience of racial identities shifts interactionally, we provide novel evidence that over the course of an interaction an individual's racial identification may shift to mirror the identification of those with whom they are interacting.[32] We explored several alternative explanations for this fluidity, and none can account for the patterns we observe. The observed fluidity is not explained solely by random measurement error and is not limited to particular types of interviewers who might be expected to account for inconsistent reporting (see Table 1, and Appendices A and C). Further, although it is possible that some interviewers may have mistaken the interviewer remarks for questions about the respondents – despite a clear prompt in the questionnaire to answer about themselves – we find evidence of racial mirroring beyond the exact matching such a mistake should produce. These data reveal consistent patterns of interviewers both exactly matching respondents and more subtly aligning responses (e.g., adding a race reported by the respondent to the interviewer's typical response), congruent with social psychological research on imitating behavior and affiliative interactions.

Future research could interview the interviewers to study how they approach building rapport with survey respondents and to further illuminate their role in the generation of survey data on race and ethnicity (see, e.g., Wilkinson 2011). We see such work as a complement to, but not a replacement for, statistical analysis of racial fluidity in survey data. Understanding whether interviewers are aware of variation in their responses and how they seek to explain it may provide

[32] This implies we would expect racial mirroring on the part of respondents as well, as they attempt to match the interviewers. Unfortunately, we cannot observe both sides of the process with these data.

insight into how conceptualizations of race as static and obvious are maintained. However, we caution against treating racial identification fluidity as something that should be 'fixed,' through admonishment in interviewer trainings or post-survey data cleaning.[33] Forcing interviewer responses to conform to static assumptions about race may provide a measure with face validity but doing so obscures the interactional nature of racial identification, and thus comes at the expense of construct validity.

Rethinking race-of-interviewer effects

That interviewers' racial identifications can be as fluid as anyone else's has implications for understanding how interviewers influence survey results in general (e.g., West and Blom 2017) and how we interpret studies on "race-of-interviewer" effects in particular. The literature on these effects generally assumes that matching respondents and interviewers by race reduces bias in survey responses by reducing social desirability bias (Krysan and Couper 2003). This view treats the interviewer's race as a fixed external factor, to which the respondent reacts, rather than a form of identification (and perception) that is subject to interactional influences.

Notably, research on race-of-interviewer effects in the GSS appears to rely on the static measure of the interviewer's race recorded on HR forms and not the repeated identifications that occur post-interview (see, e.g., An and Winship 2017).[34] For analyses that require strict

[33] We also note that the GSS principal investigators have been aware of these patterns in the data since at least 2014 – when we first contacted them about it. They continue to collect the post-interview racial identifications and we continue to find similar patterns of fluidity in the data (see Table C3).

[34] An and Winship describe their interviewer race measure as, "originally coded in the survey as a categorical variable, including Whites, Blacks, Hispanics, Asians, and others with two or more races." (An and Winship 2017: 82). These are the available categories in the HR interviewer race report.

independence of interviewer reports from interactions with respondents, the HR race measure might be preferable. Even so, it is important to acknowledge that the HR classification itself is the product of a previous interaction, when interviewers were asked to fill out a form for their employer, and the context and stakes of classification were different. Thus, the earlier measure from the HR file may not represent the interviewer's race at the time of the interview, either as they would identify it or as it would be perceived by the respondent.

Our results suggest that rather than thinking of race-of-interviewer effects as strictly exogenous influences on survey responses, we might think of the racial identifications of interviewers and respondents as mutually endogenous. Whatever response biases their identifications might indicate, how the respondent and interviewer racially identify result from a subtle interplay as both mutually negotiate their own identification, the identification of the other, and the proper schemas of interaction. In this sense, our findings also suggest that efforts to "match" interviewers and respondents by race would entail a more dynamic process than is typically acknowledged (see also O'Brien 2011).

Beyond the Survey

Our discussion so far has focused on survey interviews, but we do not expect the implications to be limited to this case. Data collection on race and ethnicity often occurs in an interactional encounter, even if only implicitly as responses are weighed against the expectations of others. Implicit and explicit interactional goals can change how participants identify or present themselves (Kang et al. 2016; Richeson and Somers 2016; Ridgeway 2009), and whether the information was self-identified or recorded as observed also shapes responses (Roth 2016; Vargas and Kingsbury 2016). Rather than viewing race as a straightforward demographic characteristic, racial categorization should be considered as crystalizing within particular interactions that subtly shape one's identification.

Indeed, our results highlight that a person's racial identification can change not only in response to macro-historical shifts in racial boundaries and categories, or in response to longer-term changes in their social position, but also within a given day depending on who they meet. This adds support to the claims of interactionists who argue for a subtler understanding of negotiated identities (e.g., Renfrow 2004). Much research on the malleability of race has focused on passing and tends to consider such changes as intentional, consequential, and costly. Rather than seeing racial fluidity solely as an intentional misrepresentation, we suggest that acts of racial presentation and identification can also reflect subtle, perhaps subconscious, efforts to align perspectives and ease interaction. That said, our findings do not imply a lack of social constraints on racial identification – stability is far more common than fluidity and some boundaries are more likely to be traversed than others – but that, within existing constraints, interactional flexibility also plays a role in shaping data on racial identification.[35]

More generally, we see processes of racial mirroring as analogous to other instances when people, consciously or not, change their presentation of self to match the situation at hand (Ambady and Weisbuch 2010). Take, for instance, the largely automatic aligning of accent and speech patterns which is hypothesized to simplify interactions and facilitate communication (Pardo 2006; Pickering and Garrod 2004). Though these transitory shifts in accent or dialect are common, people may only realize their own behavior if the deviation from their normal patterns is pointed out to

[35] It is worth noting that while racism is typically viewed as a constraint on racial fluidity, the relationship may be more complicated. It is possible, even probable given histories of 'passing', that structural racism makes fluidity more common than it would otherwise be by increasing the stakes of racial identification.

them by someone else. Racial identification is another avenue where people might be subconsciously – and often subtly – aligning to facilitate reaching shared understanding. Although the social constraints on shifting racial identification likely are stronger than the constraints on shifting speech patterns, such that shifting identification is less common, the implications remain the same. Both speech patterns and racial identifications emerge, and are best understood, in the context of dialogue.

In broader application, we might expect to find racial mirroring whenever people are motivated to try to "fit in" or bridge differences. These situations range from students interacting with one another in class (Boda 2019) to families navigating their individual and collective identities (Whitehead, Farrell and Bratter 2021). For example, the accuracy of projections for multiracial identification in the coming decades depend in part on whether parents and children identify differently when they are together versus when they are apart (cf. Bratter 2007; Harris and Sim 2002). Similarly, if married couples gravitate toward adopting a shared identity, this has implications not only for whether and when we observe relationships to be inter- or intraracial, but also for how we interpret subsequent outcomes like marital stability or psychological well-being (cf. Wong and Penner 2018). As the extensive literature on social selection and influence also suggests, homophily does not underlie all observed homogeneity (cf. Ennet and Bauman 1994; Leenders 1997; Steglich, Snijders and Pearson 2010). Rather, relationships can become more homogeneous over time – or at particular points in time – to meet affiliative interactional goals (cf. Leszczensky and Pink 2019; Melamed et al. 2020). The opposite could also be true when the goal is to maximize difference or create interactional disruption (Tavory and Fine 2020). Either way, observed racial homophily or heterophily is shaped by the interactional processes that influence both individual and collective racial categorizations.

CONCLUSION

We began with the observation that GSS interviewers do not report their racial identification consistently following each interview they conduct. Our analysis explored factors that may contribute to such response change, and we conclude that interviewers aligning their racial identifications with the identification of respondents is an important and overlooked explanation. Other explanations related to random measurement error or systematic biases, such as misunderstanding the interviewer questions to be about the respondent, particular types of interviewers, anomalies in interview timing, or particular survey years, cannot fully explain the observed pattern. Our hypothesized mechanism of racial mirroring is consistent with prior research demonstrating the many ways individuals mimic each other in affiliative interactions.

Our results have implications not only for how to conceptualize and measure race but also how to interpret research on racial inequality. As a growing body of work shows, race is not an inherent characteristic; it can be made and remade through interactions, changes in the understandings of self, and in how others are perceived. However, more research is needed on the interactional contexts that produce racial categorization. Interactions can lead to racial distancing as well as affiliative behavior such as mirroring, and stable categorization can also be an interactional accomplishment. For instance, surveys on particularly contentious issues could make spanning perceived social distance difficult, which could lead to lower-than-expected alignment rather than the higher rates we observe here. Future work should explore the potential for racial mirroring in settings where the stakes of identification are varied and the need to build rapport is less clear. Such work could help us understand the contours of social constraint and when mirroring of racial identification is most (or least) likely.

Pinpointing mechanisms and bounding effects aside, simply acknowledging that racial categorization can both influence interactions and be influenced by them should lead to further caution in when and how we use race as an explanatory tool. More than two decades ago, Zuberi (2001) admonished researchers against mistaking causes for effects in studies of race and racism, and more careful interpretation of determinants, consequences, and time-ordering in studies of racial inequality remain sorely needed. As our case illustrates: a person's "race" may not predetermine their perceptual biases, or how others will react to their presence. Interactional influence can flow in both directions, shaping how people understand themselves.

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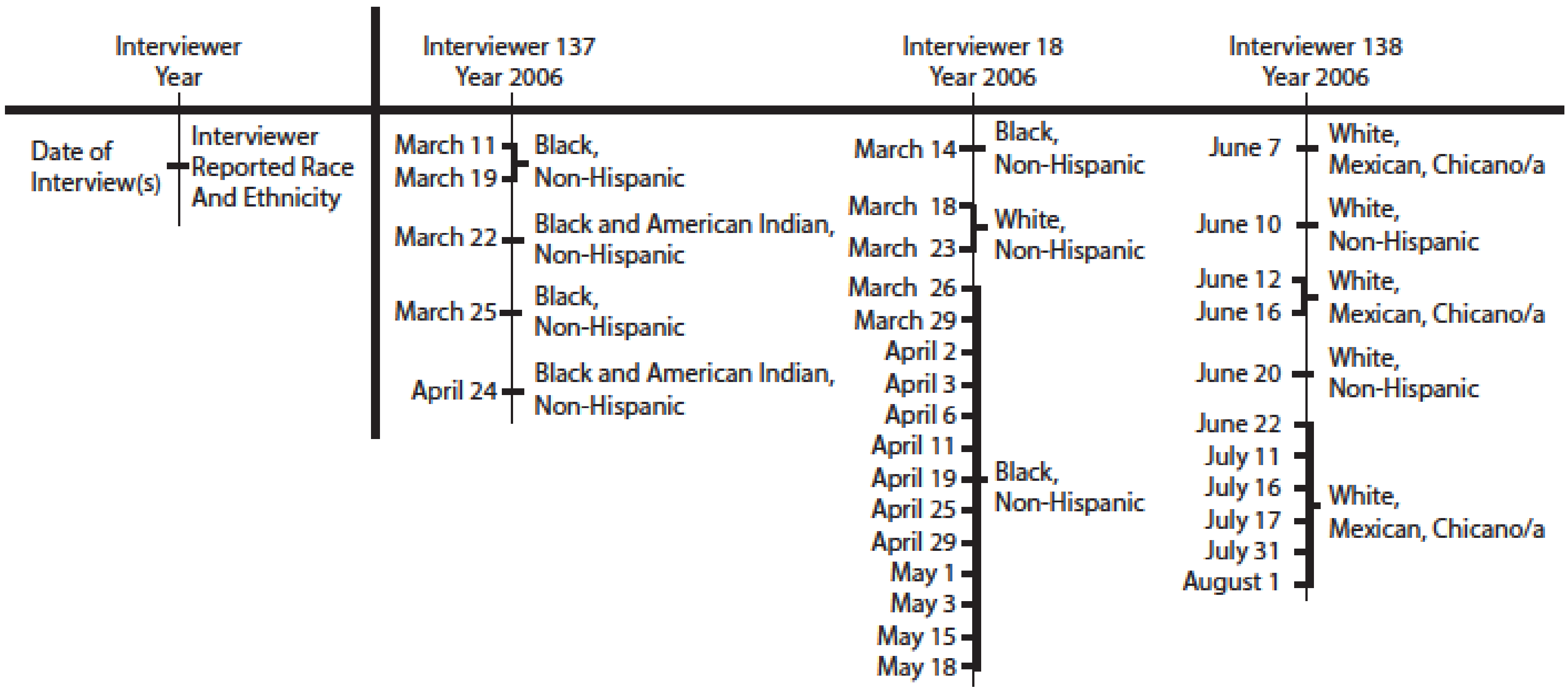
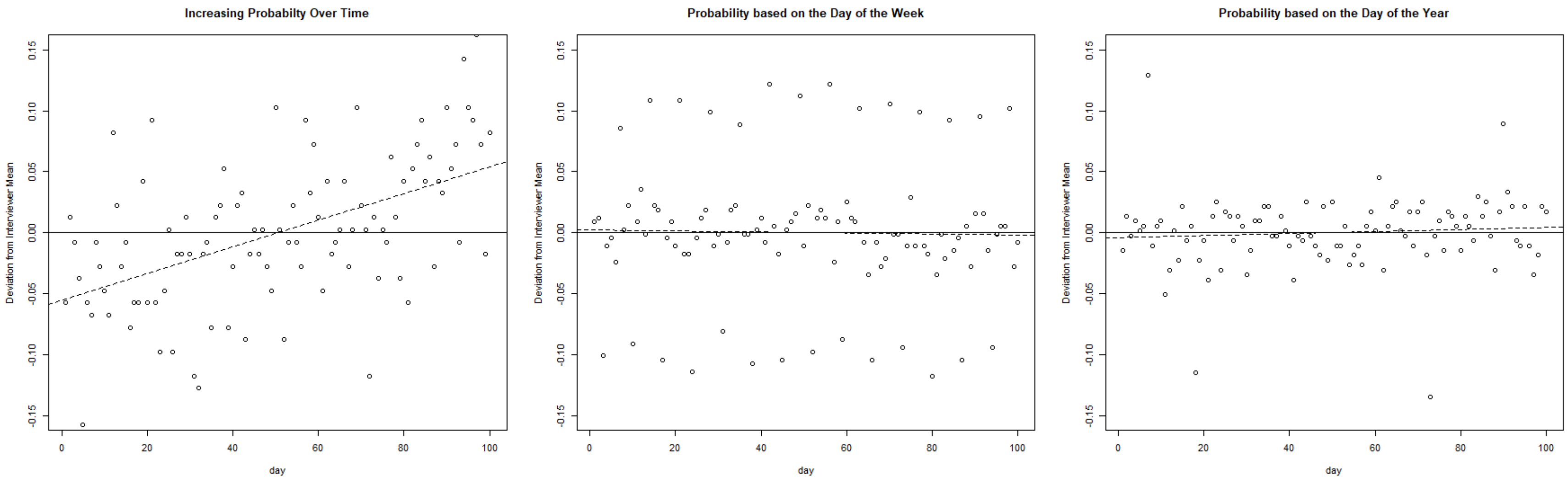
Figure 1: Sample Interviewer-year Timelines.



Source: General Social Survey.
Note: Survey years typically begin in early March.

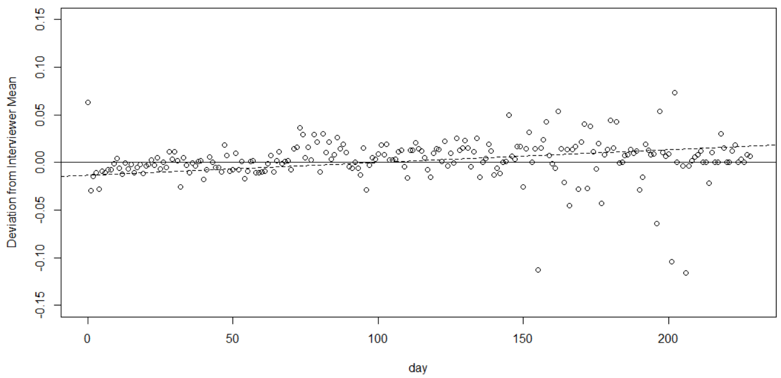
Figure 2. Ideal Type Simulations of Interviewer-year Mean-centered Probabilities of Racial Identification.



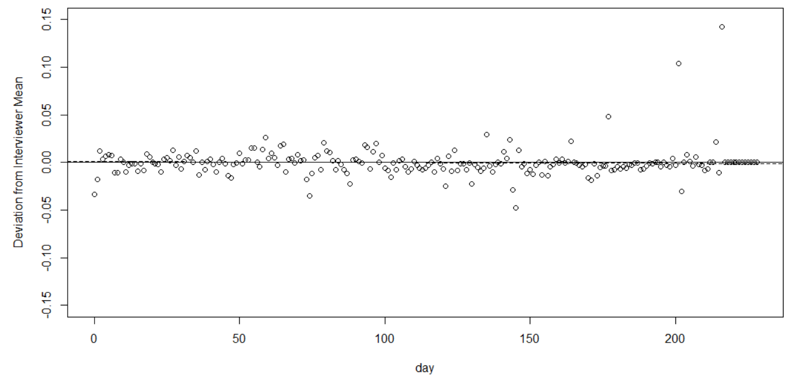
Note: Day-of-the-week and day-of-the-year plots represent plausible scenarios of systematic bias. These images provide benchmarks to compare against observed patterns in Figure 3. The zero line represents the average racial identification within interviewer-years, and deviations from these lines represent less common identifications for that interviewer-year.

Figure 3: Observed Interviewer-year Mean-centered Probabilities of Racial Identification Across the Survey Year.

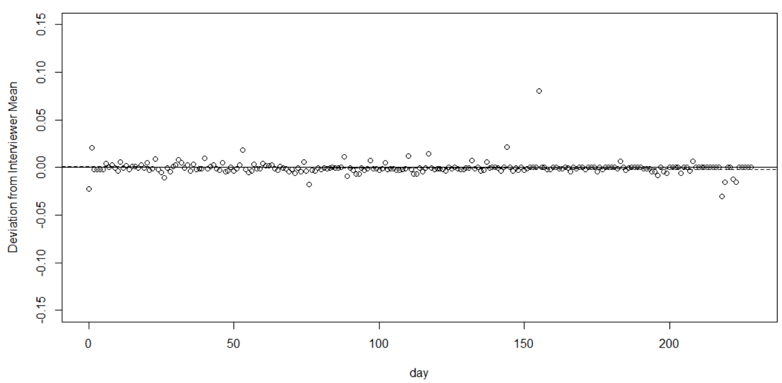
Probability of Identification as White



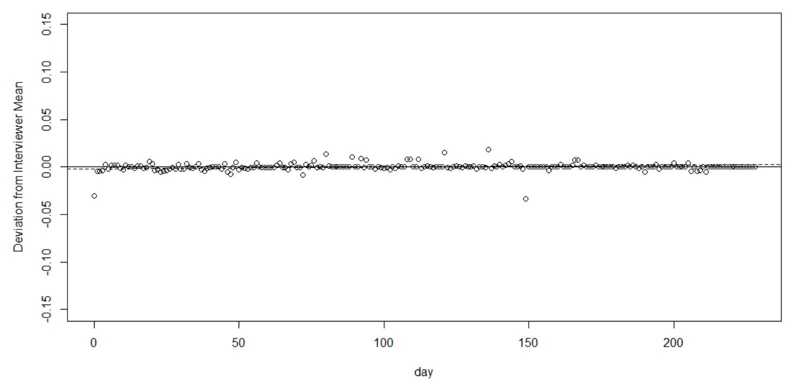
Probability of Identification as Black



Probability of Identification as Hispanic[a]



Probability of Identification as Some Other Race



Note: All plots refer to when these categories are selected alone and not in combination with other categories. ‘Day’ zero is the first interview in each survey year.
[a]Hispanic includes identification as either Hispanic race or origin.

Table 1. Interviewer-Year Characteristics by Stable or Fluid Race Identification.

	Stable Race-id	Fluid Race-id	Total
HR racial identification (static)			
White	86% (710)	14% (114)	824
Black	67% (147)	33% (73)	220
Hispanic	69% (86)	31% (39)	125
Asian	50% (9)	50% (9)	18
Two or More Races	72% (34)	28% (13)	47
Gender			
Women	80% (796)	20% (203)	999
Men	81% (195)	19% (47)	242
Mean Age (years)	53	53	
Mean NORC Tenure (years)[a]	3.30	3.35	
Interview Caseload			
At or below average (17 or fewer)	77% (629)	23% (183)	812
Above average (17 or more interviews)	77% (346)	23% (104)	450
Post-survey Hispanic origin			
Stable	83% (975)	17% (198)	1173
Fluid	35% (31)	65% (58)	89
Total	80% (1006)	20% (256)	1262

[a] A two-tailed t-test for the difference in mean NORC tenure between stable and fluid interviewers is non-significant: $t = -0.1615$, $p = 0.8718$.

[b] Here, we account for identifying as Hispanic by race or origin, which is not mutually exclusive with the other race categories.

Table 2. Frequency of Racial Fluidity Across Time Windows.

Survey Year	Same Day	Five Days	Ten Days	Fifteen Days	Thirty Days
5%	4.2%	4.6%	4.8%	4.8%	4.8%

Source: General Social Survey, 2004-2018. Frequencies of response change are calculated among the set of consecutive interviews in which changes are possible (e.g., the ‘Same Day’ percentage is among days where multiple interviews were conducted, ‘Ten Days’ corresponds to multiple interviews conducted anytime from on the same day through 10 days apart). When multiple interviews were conducted in a single day, ties are broken by computing all possible orderings and taking the average proportion of changes across them.

Table 3. Cross-tabulation of Interviewer and Respondent Racial Identification Among Interviewers Who Tend to Identify as White.

		Respondent Race								
		Asian Indian	Black	Black and AIAN	Chinese	Hispanic	Other Asian	White	White and AIAN	Total
Interviewer Race	Asian Indian	75% (9)	0	0	0	0	0	25% (3)	0	100% (12)
	Black	0	84% (87)	5% (5)	0	0	0	12% (12)	0	100% (104)
	Black and AIAN	0	0	100% (6)	0	0	0	0	0	100% (6)
	Black and White	0	100% (4)	0	0	0	0	0	0	100% (4)
	Hispanic	0	5% (1)	0	10% (2)	65% (13)	0	20% (4)	0	100% (20)
	Some other race	0	25% (1)	0	0	50% (2)	25% (1)	0	0	100% (4)
	White	1% (108)	10% (1576)	1% (102)	1% (100)	4% (540)	<1% (46)	81% (12523)	3% (424)	100% (15419)
	White and AIAN	0	0	0	0	0	0	37% (7)	63% (12)	100% (19)
	White and Hispanic	0	17% (1)	0	0	33% (2)	0	50% (3)	0	100% (6)

Source: General Social Survey, 2004-2018.
Note: Racial identification among interviewer-years with at least 65% monoracial White identifications. Row percentages are shown, with counts in parentheses. Rows or columns with fewer than 5 total non-monoracial White reports not shown (all 5 are not necessarily visible in this abbreviated table). Outlined cells represent exact matches, cells filled gray represent aligned responses.

Table 4. Linear Probability Models Predicting Interviewer Racial Identification by Characteristics of the Interview.

	Interviewer Identifies as…					
	White	Black	Asian Indian	Chinese	Some Other Race	Hispanic[a]
Respondent identifies as same race	0.055***	0.063***	0.090***	0.057**	0.050	0.037***
	(7.931)	(6.283)	(3.496)	(2.843)	(1.907)	(3.662)
Interviewer identifies as Hispanic origin	-0.016	-0.127***	-0.023*	-0.010	0.042	
	(0.282)	(-3.666)	(-2.256)	(-1.152)	(1.662)	
Interview conducted in Spanish	0.015	0.004	-0.001	0.002	0.006	0.043**
	(1.196)	(0.640)	(-0.629)	(1.839)	(1.015)	(2.922)
Respondent's spouse was present	0.001	0.001	-0.000	-0.000	0.000	0.003
	(0.474)	(0.601)	(-0.178)	(-1.234)	(0.393)	(1.592)
Respondent has never married	-0.005	0.005*	-0.001	0.000	-0.000	0.000
	(-1.819)	(2.319)	(-1.913)	(0.595)	(-0.533)	(0.243)
Respondent's Age (decades)	-0.001*	0.001	0.000	0.000	0.000	-0.001
	(-2.348)	(1.898)	(0.347)	(0.020)	(0.026)	(-1.868)
Population (logged)	-0.001*	0.001	0.000	0.000	0.000*	0.001
	(-2.023)	(1.216)	(0.223)	(0.508)	(2.496)	(1.543)
Interviewer-year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: Results from models predicting differences within a given interviewer for a particular survey year, t-statistics accounting for clustering within interviewer-year in parentheses. Each model has 20,619 observations over 1,259 interviewer-years.
Models additionally control for respondent sex, which was non-significant.
*** p<0.001, ** p<0.01, * p<0.05
[a] In this model we predict identifying as Hispanic *either* by race or origin. Results are similar and statistically significant if we use only race or only origin.

Table 5. Linear Probability Models Predicting Interviewer Racial Identification Excluding Interviewers Who Always Exactly Match the Respondent.

	Interviewer Identifies as…					
	White	Black	Asian Indian	Chinese	Some Other Race	Hispanic[a]
Respondent identifies as same race	0.054***	0.063***	0.070**	0.057**	0.050	0.037***
	(7.825)	(6.283)	(2.983)	(2.843)	(1.906)	(3.671)
Interviewer-year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: Results from models predicting differences within a given interviewer for a particular survey year, t-statistics accounting for clustering within interviewer-year in parentheses. Models are analogous to those shown in Table 3. Each model has 19,651 observations over 1,087 interviewer-years. Controls not shown.
*** $p<0.001$, ** $p<0.01$, * $p<0.05$
[a] In this model we predict identifying as Hispanic *either* by race or origin. Results are similar and statistically significant if we use only race or only origin.