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Racial animosity and black financial advisor underrepresentation

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Abstract

This study provides compelling evidence for Black underrepresenation in the financial advisor industry. Using a dataset of all U.S. securities-licensed individuals ($N = 642{,}543$), we first estimate the racial and ethnic composition of the industry using an algorithm that accounts for name, gender, and location. Second, we use a dataset enhanced by a commercial vendor to restrict the analysis to only those identified as working as financial advisors ($n = 237{,}435$). Using Google search volume for a racial epithet as a proxy for area racism, we find that greater racism in a market is associated with greater Black advisor underrepresentation. Overall, we estimate at the individual level that 10.1% of financial advisors are Black (relative to 13.4% of the U.S. population). Furthermore, our results suggest marke-tlevel racial animosity toward Blacks is negatively associated with Black advisor represnetation. We estimate a difference of 0.9 percentage points when comparing markets with the highest and lowest levels of animosity. For the average market with an estimated 11.4% Black advisor representation, an increase of 0.9 percentage points would represent a 7.9% increase in Black advisor representation.

KEYWORDS
discrimination, financial advisors, racial attitudes, racial bias, underrepresentation

JEL CLASSIFICATION
J44, J71, R10

1 | INTRODUCTION

Despite an industry-wide concern about the lack of diversity (Mohrman-Gillis, 2018), a reliable estimate of Black representation among financial advisors is still needed. The Bureau of Labor Statistics (BLS, 2020) estimates 6.9% of personal financial advisors are Black (compared to 13.4% of the US population), whereas Data USA's (n.d.) estimate is between 4.7% and 6.7%.

We therefore seek to provide a refined estimate based on race and ethnicity estimates for every client-facing financial advisor in the US. We employ a classification algorithm used by Imai and Khanna (2016), which provides unique racial and ethnic estimates for each individual licensed within the industry based on their name, gender, and location. We then apply this to a dataset enhanced by a commercial vendor to include job role classifications, allowing us to estimate industry demographics among those specifically identified as client-facing financial advisors ($n = 237{,}435$).[1]

Second, we look for real-world correlates of Black financial advisor representation, by exploring whether representation is correlated with local racial attitudes. Measuring racial attitudes can be difficult, as consumers may not be comfortable sharing racial preferences or prejudices in consumer surveys (e.g., Britton, 2014; Prudential, n.d.). In the present study, we therefore use Google search data (Harris & Yelowitz, 2018; Stephens-Davidowitz, 2014) to examine whether area racism against Blacks is associated with greater underrepresentation of Black advisors within U.S. markets. We hypothesize (H_1) that area racism, as reflected in Google search volume for an anti-Black racial epithet, will be negatively associated with representation of Black advisors within U.S. markets.

2 | BACKGROUND

Past theorizing on the factors contributing to underrepresentation in different occupations has highlighted the role of both institutional practices within the organization (e.g., managerial discrimination, biased recruitment, discrimination in team formation; Bielby, 2012) and influences outside the organization, including local factors (e.g., the pipeline problem, applicants' social networks, and demographics) and consumer discrimination (i.e., clients' racial or gender preferences when selecting a financial advisor; Reiter et al., 2022). A number of studies have explored how these different factors contribute to underrepresentation in different occupations.

Lyons-Padilla et al. (2019), for example, conducted an experimental study with asset allocators to study the effect of racial bias in institutional investment decisions. They found that asset allocators preferred funds led by White management teams over Black teams when the funds were high-performing, but preferred the Black-led teams over the White-led teams in the low-performing fund condition. As asset allocators preferred the high-quality funds overall, this bias against high-performing Black fund managers is advanced as a contributor to their underrepresentation in financial management.

Cohen and Huffman (2007) demonstrate how factors *outside* the workplace can contribute to Black underrepresentation in managerial positions across a number of industries, including the finance industry. They found, across four different measures of representation, greater Black managerial underrepresentation in geographical areas with a greater proportion of Black residents. This work aligns with earlier work showing that a greater proportion of Black residents in an area is associated with greater earnings inequality (Tienda & Lii, 1987) and job-level racial segregation (Huffman & Cohen, 2004). We suggest an important but unexplored feature of the local environment that could be associated with racial underrepresentation in personal finance advising is area racism.

Studying the impact of area racism on financial advisor representation is difficult because individuals self-censor their responses on surveys due to social desirability bias (Krumpal, 2013). Respondents are therefore unlikely to report an explicit racial bias. Reiter (2020) found that despite White and Black consumers perceiving themselves as more similar to White and Black advisors, respectively, consumers did not express racial preferences regarding advisors they would hire, take advice from, or trust. Additionally, when asked explicitly for their attitudes, White consumers rated Black advisors as more competent than White advisors (Reiter, 2020). In contrast, using banking data that was not dependent upon survey responses, Black et al. (2004) found individuals preferred to use banks that were owned by individuals of the same race.

To work around this potential self-censoring of self-report data, alternative unobtrusive measures of racial attitudes have been developed. Stephens-Davidowitz (2014) developed a measure of racial animus from Google search data using a racial epithet for Blacks (Stephens-Davidowitz, 2014). He found the use of the "N-word" in Google searches in a geographic area predicted President Obama's vote share controlling for the previous Democratic candidate's results, accounting for four to six percentage points in the national vote (Stephens-Davidowitz, 2014). This measure also strongly correlates with other measures of prejudice, including the General Social Survey measure of support for a law banning interracial marriage. Later research using this measure demonstrated a number of real-world correlates, including Black mortality rates (Chae et al., 2015), birth outcomes for Black parents (Chae et al., 2018), self-rated health (McKetta et al., 2017), racial bias in police shootings (Ross, 2014), and voting patterns. This research suggests this internet search-based measure of racism at the metropolitan market level is thus a valid reflection of racism in a geographic area.

The present study therefore employs data from several sources to provide a novel estimate of the racial composition of the financial advisor industry, and then uses this estimate to investigate whether there is an association between the levels of racially charged Google search queries in a market area and Black advisor underrepresentation.

3 | METHODS

3.1 | Advisory industry characteristics and racial composition estimates

First, we determine the racial composition of advisors in each market area. To determine the racial composition of the advisory industry within each metropolitan market, we first use job classifications to identify and exclude those in the advisory industry without the classification of "advisor." Using the R statistical package "wru" ("Who are you?") and using 2020 Census data, we then employ an extended Bayesian algorithm to predict an individual advisor's race conditional on first name, surname, gender, and zip code (Imai & Khanna, 2016). Our method mirrors that of Imai & Khanna by estimating a probability that a given individual is a member of a given racial group, as follows:

$$\Pr(R_i=r|S_i=s,G_i=g,X_i=x,F_i=f) = \frac{\Pr(G_i=g,X_i=x|R_i=r)\Pr(R_i=r|S_i=s,F_i=f)}{\sum_{r'\epsilon\mathcal{R}}\Pr(G_i=g,X_i|R_i=r')\Pr(R_i=r'|S_i=s,F_i=f)} \quad (1)$$

where an advisor i is a member of racial group r, g is the advisor's geolocation, s is the advisor's surname, f is the advisor's first name and x is the advisor's gender. We let G, F, S and R represent the set of all geolocations, first names, surnames and racial groups. The algorithm is "extended" because a previous algorithm used in healthcare used only surnames and geolocation (Elliot, et al. 2009). Imai and Khanna (2016) used this method on voter data to determine the racial composition of voters in a particular district, by using Census data containing race, first name, surname, gender, age and zip code. More specifically, because the Census identifies race, along with first names, surnames, zip code and accounts for generational changes in naming (Fryer & Levitt, 2004). Thus, the algorithm avoids falsely identifying those with "white"-sounding names as White and those with "black"-sounding names as Black. Within the voter record data, the false positive rate for identifying an individual as Black using these parameters in the algorithm is 2.9%.

We apply the same approach on our advisor dataset. Conditional on first name, surname, gender, we estimate the racial composition of a given market area. The proportion of households in each market that are White (*prop_whi*) or Black (*prop_bla*) is determined from the Census data and estimates of the proportion of advisors in each market that are White (*propa_whi*) or Black (*propa_bla*) as the mean probability as provided by the algorithm of a given individual, conditional on the above items, being assigned to either race.

Previous studies using racial prediction methods (Fraga, 2016) use informal, Likert-type schemes with significant information loss based upon self-report information of race. Utilizing a probabilistic Bayesian model provides a more rigorous approach to race prediction. In particular, our use of Census data provides an increased level of robustness. The wru package itself has been validated by the R user community in numerous test cases and has been updated by the authors as feedback was provided.

3.2 | Market-level zip code mapping and demographics

Second, zip code-to-market mapping is facilitated by data made freely available online by a commercial vendor.[2] Third, zip code data on household incomes and race are reported by the Census Bureau's 2018 American Community Survey, which is the most recent data available for our analyses.[3] We bifurcate each zip code by household income and the proportion of households that self-identify as a certain race, either White or Black. As we would expect relatively more affluent communities to have more financial advisors, we create two measures of household affluence for each metropolitan market: one for general affluence, regardless of race (*GenAff*), and one for Black households (*BlackAff*). We employ the minimum household income level of $100,000 from the CFP Board's Mass Affluent Initiator criteria as our threshold to be considered affluent.[4] For each market, general affluence (*GenAff*) and Black affluence (*BlackAff*) is the proportion of total households or Black households, respectively, that meet the threshold. Fourth, we use a dataset prepared by a commercial vendor, Discovery Data, containing information on all securities-licensed individuals in the United States, including information such as advisor names (first name and surname), gender, location (home zip codes), and job role classifications.

3.3 | Area racism

Finally, to measure area racism, we use an animosity index (*Animus*; Stephens-Davidowitz, 2014) that measures Google search volume for a racial epithet by market. The creation of this measurement is consistent with other search terms over time across many regions (Botezat, 2017). The original measure of racial animosity was constructed using Google Trends data for search queries for the N-word (ending in -er) and its plural (herein "*query*") from 2004–2008, finding that the measure negatively predicted Barack Obama's vote share. Constraining the methodology to a single spelling of this term (the most widely known racial slur in the English language; Kennedy, 2003) avoids data mining (e.g., testing a variety of derogatory terms).

Because the Google Trends API originally employed is no longer available, we made a number of updates to the methodology using the current public-facing Google

Trends website. First, Stephens-Davidowitz (2014) used a computer program to sample the Trends API 5000 times. Since we manually collect our data, the updated measure is the average of three samples.[5] Second, Trends does not report data for markets with very low search volume for specific queries. We therefore omit markets from our sample with unreported values from Trends. This reduces the sample from 206 with the original measure to 188 with our updated measure.

To construct our measure of racial animosity, we query Google Trends for the 5-year period beginning January 1st, 2015 by state for *query* and rank the states, with a rank of 1 being assigned to the state with the highest search value (i.e., "N-word+N-words" search volume as a proportion of that state's total search volume). We then repeat the query at the market level. To make comparisons between markets across states, we calculate a weight, w, for each state, i, as

$$w_i = \frac{rank_i}{51} \tag{2}$$

and a weighted animus value for each market, j, within each state as.

$$animus_j = value_j(1 - w_i).^6 \tag{3}$$

Finally, we average weighted $animus_j$ over three samples for each market to arrive at our measure.

3.4 | Regression variable selection

As noted previously, prior theorizing on the factors contributing to occupational underrepresentation has focused on both institutional practices (e.g., managerial discrimination) and influences outside of an institution (e.g., consumer discrimination). While the present study cannot speak to the specific manifestation of racial animosity either internal to or external to an institution, it is nonetheless plausible that greater levels of racial animosity within an area could also contribute to greater managerial or consumer discrimination. Therefore, we include area racism as the key independent variable within our analysis, with the expectation that area racism will be negatively associated with representation of Black advisors within U.S. markets (H_1).

However, area racism is not the only factor one might expect, ex ante, to be correlated with Black financial advisor representation within a geographic area, or even the factor one might expect to be most strongly correlated with Black financial advisor representation. One major factor anticipated in this study is the general demographic makeup of a region. For instance, one might expect a higher percentage of Black advisors to be working in a region that is 50% Black compared to a region that is 5% Black. Therefore, we include the proportion of a population that is Black as a control variable in our analysis and anticipate that this variable will exhibit one of the strongest relationships with Black advisor representation.

Another factor that we anticipate being relevant to control for is the general affluence of an area. Individuals of different socio-economic status may engage in either consumer or managerial discrimination differently. Additionally, we anticipate that levels of Black affluence within an area will be relevant to control for separately. Prior research has indicated that financial advisors in the U.S., regardless of their business models, are largely servicing consumers within the top quintile of wealth (Tharp, 2020). In light of other prior research that has indicated that consumers may have a preference to work with financial institutions that include more individuals of their own race (Black et al., 2004), we anticipate that levels of Black affluence within an area may also be correlated with Black financial advisor representation. In other words, even within areas that otherwise have similar percentages of their populations that are Black, one might expect, ex ante, that areas with higher levels of Black affluence may exhibit higher levels of Black advisor representation.

4 | RESULTS

4.1 | Industry estimates

Summary statistics for all securities-licensed professionals are reported in Table 1. Out of 642,543 securities-licensed individuals reported by Discovery Data, over 237,000 (about 37%) have the job classification containing "advisor."[7] Of the approximately 237,000 financial advisors, about 80% are male and 20% are female.

Estimated racial and ethnic compositions of the full sample of securities-licensed professionals, all individuals classified as financial advisors, and additional subsamples of professionals are reported in Table 2. Overall, the algorithm used in this analysis estimates that, at the individual level, 10.1% of financial advisors are Black (versus 13.4% of the U.S. population), which is consistent with other estimates of underrepresentation of Black advisors. The full sample size of 576,533 individuals reported in Table 2 is less than the 642,543 individuals reported in Table 1 due to incomplete data, which made some individuals' ethnicity and race unclassifiable. We use the full sample reported in Table 2 in all subsequent analysis.

TABLE 1 Financial advisor descriptive statistics

	All securities-licensed individuals		Financial advisors	
	($N = 642{,}543$)		($n = 237{,}435$)	
Measure	*n*	%	*n*	%
Gender				
Male	474,039	73.8%	189,656	79.9%
Female	168,504	26.2%	47,779	20.1%
Licenses and designations				
CFP®	64,885	10.1%	42,170	17.8%
Series 6	190,868	29.7%	84,374	35.5%
Series 7	413,360	64.3%	164,278	69.2%
Series 65	140,796	21.9%	77,612	32.7%
Series 66	174,313	27.1%	87,939	37.0%
Insurance licensed	294,756	45.9%	179,995	75.8%

Note: This table reports descriptive statistics for the sample of all securities-licensed individuals obtained from Discovery Data and the subsample of individuals identified as financial advisors.

TABLE 2 Estimated racial and ethnic composition among various subsamples

	Full sample	Financial advisors	Insurance licensed advisors	Admin. Staff	Planning specialist	Portfolio manager	Research	Trading desk
	($N = 576{,}533$)	($n = 237{,}435$)	($n = 179{,}995$)	($n = 5299$)	($n = 7420$)	($n = 9677$)	($n = 10{,}956$)	($n = 6696$)
White	72.9%	74.3%	75.2%	73.8%	76.5%	76.1%	71.6%	73.3%
Black	9.8%	10.1%	10.2%	10.3%	10.0%	9.4%	8.8%	8.3%
Hispanic	8.8%	8.2%	7.6%	8.8%	6.7%	6.3%	7.8%	8.0%
Asian	6.0%	4.9%	4.5%	4.6%	4.3%	5.7%	9.3%	7.9%
Other	2.5%	2.5%	2.5%	2.5%	2.5%	2.5%	2.5%	2.4%

Note: This table reports the estimated racial and ethnic composition of various subsamples within our full sample of securities-licensed individuals. Groups included in the table above are not mutually exclusive. Individuals could have multiple classifications (e.g. "Financial Advisor" and "Portfolio Manager").

TABLE 3 Market-level variables ($n = 188$)

Variable	Mean	Std. dev.	Median	Min	Max
Animus – original	0.64	0.20	0.62	0.26	1.55
Animus – updated	0.43	0.24	0.43	< 0.00	0.98
Proportion White (*White*, %)	75.53	9.63	77.14	14.33	86.83
Proportion Black (*Black*, %)	11.45	3.50	10.47	2.03	20.63
Proportion of White Advisors (*WhiteAdv*, %)	76.53	9.00	77.95	14.52	87.00
Proportion of Black Advisors (*BlackAdv*, %)	11.44	3.60	10.37	1.89	21.56
General Affluence (*GenAff*, %)	26.02	8.19	24.43	12.71	53.42
Black Affluence (*BlackAff*, %)	1.07	1.15	0.73	0.00	7.60

Note: This table reports descriptive statics for the market-level variables used in our analyses. Affluence is defined as household income of $100,000 or greater.

Summary statistics for market-level variables are reported in Table 3. The average market has a household composition of about 76% White and 11% Black, with approximately 26% of all households, and 1% of Black households, being classified as affluent. The average market showed an estimated 11.4% Black advisor representation.[8]

4.2 | Associations between area racism and representation

To investigate whether area racism is associated with Black underrepresentation in the financial advisor industry, we estimate Equation (4), where for metropolitan market j, the dependent variable is the proportion of

TABLE 4 Regression results predicting Black advisor representation

Model	I	II	III	IV
Intercept	0.001	−0.002	−0.002	−0.001
	(0.25)	(−0.45)	(−0.47)	(−0.48)
Animus	−0.007*	−0.008**	−0.008**	−0.008*
	(−2.26)	(−2.66)	(−2.67)	(−2.57)
Black	1.033***	1.045***	1.033***	1.041***
	(47.29)	(45.84)	(39.52)	(46.19)
GenAff	0.002	0.001	0.001	0.002
	(0.25)	(0.13)	(0.11)	(0.21)
BlackAff	−0.082	−0.052	−0.043	−0.045
	(−1.22)	(−0.77)	(−0.65)	(−0.67)
N	188	188	187	187
Adj. R^2/ Pseudo R^2	95.40%	95.45%	95.74%	95.73%
F (d.f.)	971.2 (183)	981.6 (183)		
Wald χ^2 statistic			0.51	0.16
(*p*-value)			(0.474)	(0.690)

Note: Model I is estimated with OLS and the original measure of animosity. Models II-IV employ the revised animosity measure and are estimated with OLS (II) or generalized spatial 2SLS with spatial dependence of the dependent variable (III) or the error term (IV). Adjusted R^2 is reported for OLS models, while pseudo R^2 is reported for spatial 2SLS models. *t*-statistics are reported in parentheses. Statistical significance at the 0.1%, 1%, and 5% levels are denoted ***, **, and *, respectively.

Black advisors (*BlackAdv*), and the regressors are the proportion of a market that is Black (*Black*), general affluence (*GenAff*), Black affluence (*BlackAff*), and racial animosity toward Blacks (*Animus*). We report OLS estimates of Model I (original measure of *Animus*) and Model II (updated measure of *Animus*) in Table 4.

$$BlackAdv_j = \alpha + \beta_1 Black_j + \beta_2 GenAff_j + \beta_3 BlackAff_j + \beta_4 Animus_j + \varepsilon_j \quad (4)$$

The results in Table 4 suggest that both the proportion of Black households (*Black*) and racial animosity toward Blacks (*Animus*) have strong associations with the proportion of Black advisors (*BlackAdv*) across our sample markets. The coefficients on *Black* of 1.033 and 1.045 in Models I and II are statistically significant at the 1% level and indicate that for every 1 percentage point increase in the proportion of Black households, there is an approximately 1.03 and 1.05 percentage point increase in Black advisor representation, respectively. The coefficient estimates on general affluence (*GenAff*) and Black affluence (*BlackAff*) are positive and negative, respectively, but neither is statistically significant for either Model I or II. *Animus*, however, is negatively associated with Black advisor representation, with an estimated coefficient of −0.007 that is significant at the 5% level in Model I and a coefficient estimate of −0.008, which is significant at the 1% level in Model II. To put these results in economic terms, the range in *Animus* of 1.29 (or 0.98 for the updated measure) indicates a potential increase in Black advisor representation of 0.9 (0.8) percentage points, moving from the community with the most animosity to the least. For example, for the average metropolitan market with 11.4% Black advisors, an increase of 0.9 percentage points would represent a 7.9% increase in Black advisor representation. The results reported in Table 4 indicate that estimating Equation (4) with our sample explains over 95% of the variation in Black advisor representation across our sample markets.

As our sample comprises 188 market areas within the contiguous 48 United States and Hawaii, results from estimating Equation (4) with OLS as reported in Models I and II of Table 4 do not account for possible spatial correlation between geographic areas, which could bias standard errors downward. As illustrated in Figure 1, animosity toward Blacks is not randomly distributed around the U.S. We therefore conduct a robustness analysis for a spatial correlation in *BlackAdv* (Model III) and in the error terms (Model IV). Rather than use a proportional model (Montolio & Planells-Struse, 2015), we created a contiguity spatial weight matrix with a shapefile for the markets (Sood, 2016), which reduces the sample size to 187 markets due to data availability, and re-estimate Equation (4) with a generalized spatial two-stage least squares approach. Allowing for spatial correlation of the dependent variable (*BlackAdv*) or the error terms does not quantitatively change our core results. The magnitudes of the estimated coefficients on *Animus* of −0.008 and *Black* of between 1.033 and 1.041 in Models III and IV, respectively, align with results in Models I and II. The estimates on *Animus* and *Black* are also statistically significant at conventional levels in these models.[9] The Wald tests reported for Models III and IV in Table 4 reject the hypothesis of spatial correlation in the dependent variable and error terms, respectively.

5 | DISCUSSION

This study provides the first estimate of industry racial and ethnic composition based on a classification algorithm applied to each securities-licensed individual in the financial services industry. This yields an estimate of 9.8% Black representation across all securities-licensed individuals in the financial services industry. Using the enhanced

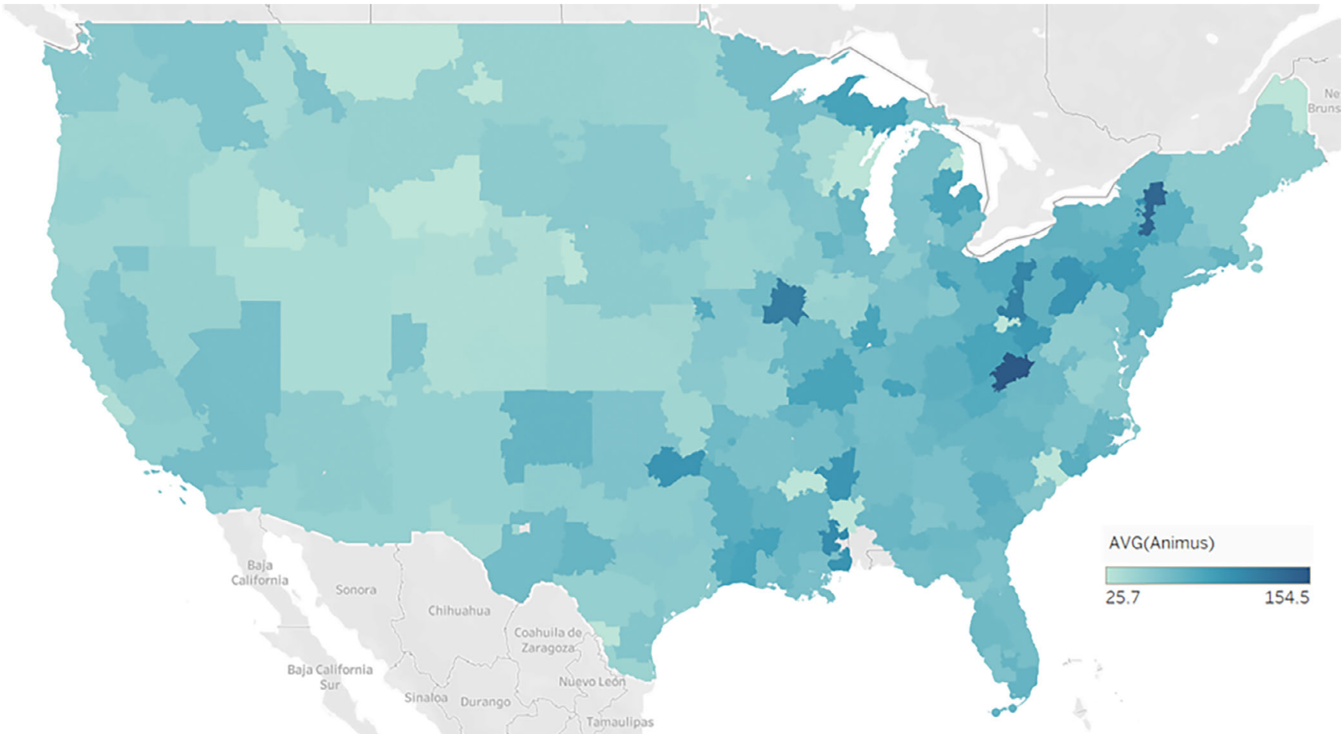

FIGURE 1 Geographic variation in racial animosity toward Blacks. (Darker blue indicates greater levels of racial animosity toward Blacks).

dataset with job classifications by industry channel, we are further able to provide unique estimates of racial and ethnic composition across different industry channels. For instance, we estimate that Black representation is highest among administrative staff (10.3%) and lowest among those working on trading desks (8.3%). The estimate that 10.1% of financial advisors are Black is significantly higher than previous estimates. To put these findings in a broader context, Addo and Beverly (2022) report the racism experienced by Black Americans when seeking wealth management services and note the need for racial diversity in the financial planning profession and for firms to offer services tailored to the needs of Black clients.

The differences observed between industry channels are broadly consistent with the findings of Tharp et al. (2021) that omitting job classifications from studies using industry regulatory data—as is commonly done in most studies of the financial services industry today—is a significant limitation for studying minority representation more broadly. For instance, although we estimate that Asians are overrepresented among securities-licensed individuals overall (6.0% overall versus 5.5% in the U.S. population; see U.S. Census Bureau, 2019), they are underrepresented among financial advisors (4.9% versus 5.5% in the U.S. population). This illustrates the importance of taking the steps that we did in this study to differentiate financial advisors from the industry as a whole.

These findings provide much-needed information for a pressing issue. Congressional hearings have been held examining the lack of diversity in financial services, and both the EEOC and GAO have conducted studies on racial inclusion within the financial services industry (Miller & Tucker 2013). Private firms (e.g., Edward Jones; see Schoeff Jr., 2019) and industry organizations (e.g., CFP Board; see CFP Board of Standards, 2021) have instituted policies aimed at promoting greater racial and ethnic inclusion. The present research provides an improved estimate of the magnitude and correlates of Black underrepresentation in the financial services industry.

One important correlate of Black underrepresentation that is highlighted in this work is area racism. We find greater market-level racial animosity toward Blacks is associated with greater underrepresentation of Black financial advisors in that area. This relationship is both statistically and economically significant. Firms that are interested in promoting diversity, equity, and inclusion may want to consider the additional barriers associated with markets with higher levels of racism. For example, Black financial advisors working in areas with higher levels of anti-Black prejudice may not get the same outcomes as a White advisor with an equal marketing budget.

There are a number of limitations to the present study. First, the previously-calculated false positive rate for identifying an individual as Black in the voter record data using this algorithm was 2.9% (Imai & Khanna, 2016). However, even subtracting this potential over-identification, our overall estimate of Black advisor representations higher than other estimates (e.g., see the BLS estimate of 6.9%; Bureau of Labor Statistics, 2020). Our estimate is, to the best of our knowledge, the first based on the name, gender, and location of all individuals within the industry, using a more conservative classification of financial advisors. Second, whereas our study examined associations between area racism and representation, we did not examine causal relationships in either direction. Experimental approaches (e.g., Lenz & Mittlaender, 2022) could be used to follow up on these correlational results.

6 | CONCLUSION

The present study provides compelling evidence for Black underrepresentation in the financial industry. The algorithm used in this analysis estimates that 10.1% of financial advisors are Black (relative to 13.4% of the U.S. population). Furthermore, our results suggest market-level racial animosity toward Blacks is negatively associated with Black advisor representation.

While this analysis cannot speak to causal relationships between an area's racial animosity toward Blacks and Black advisor underrepresentation, we believe both managerial discrimination (an institutional practice within an organization) and consumer discrimination (an influence outside of an organization) are two potential mediators that warrant further examination. In contrast to prior survey research that did not find evidence of consumer discrimination via self-report (e.g., Reiter et al., 2022), the results of our analysis using an unobtrusive measure of area racism and actual representation suggests there may be an influence of consumer discrimination against Black advisors. Managerial discrimination in the hiring and firing of financial advisors is another potential mechanism that could also contribute to this underrepresentation of Black advisors and warrants further investigation.

Our analysis also does not address the racial wealth gap. Given most advisors charge a percentage of assets under management (AUM), and companies have been reported to use race/identity matching to match clients to their advisor (Bielby, 2012), the racial wealth gap may both contribute to and be perpetuated by this underrepresentation of Black advisors.

Given the efforts to address the problem of underrepresentation of Black advisors within the financial advisory industry (CFP Board Center for Financial Planning, 2018), these findings may also suggest the problem may ultimately need to be addressed at the market or societal level. Attitudes of racial prejudice in areas may make it more difficult for stakeholders in the field to reduce the underrepresentation of Black advisors. Policymakers and other community members may need to incorporate strategies to positively influence their market areas away from racial prejudices.

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CONFLICT OF INTEREST STATEMENT

Michael Kothakota is the Head of Research at CFP Board and is a member of its Executive Leadership Team. This study was completed prior to his appointment at CFP Board and he received no compensation for his role. While Financial Planning Review is sponsored by CFP Board, Michael Kothakota has no oversight with respect to the journal.

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ENDNOTES

[1] This estimate is lower than the leading industry estimate of 311,305 (Fazzi, 2018) because the commercial data vendor we use, Discovery Data, classifies individuals as "unknown" if someone cannot be positively identified as an advisor (e.g., through company websites, social media profiles, or other means), which has been shown to be less biased (Tharp et al., 2021).

[2] We use the terms "metropolitan market" and "market" to refer to media markets delineated by commercial vendors for advertising purposes. Google Trends reports data by Designated Market Area (DMA), which are a proprietary geographic delineation of media markets created by Nielsen Holdings plc. As our second data source, a free alternative to DMAs is the Designated Market Maps (DMMs) available from Truckads.com, which provided the requisite zip code correlations. DMMs and DMAs are 99% similar (https://www.truckads.com/press-releases/Nielsen-DMA-ZIP-codes-vs-Truck-Ads-ZIP-codes.htm).

[3] We use the term "zip code" loosely. Zip codes and ZCTAs are trademarks of the U.S. Postal Service and U.S. Census Bureau, respectively. ZCTAs are designed to be aerial geographic representations of Postal Service zip codes. Per the Census Bureau, the ZCTA codes are equivalent to the zip codes for most areas, thus we use ZCTAs in mapping Census data to market data. https://www.census.gov/programs-surveys/geography/guidance/geo-areas/zctas.html

[4] https://www.cfp.net/news/2021/03/public-awareness-campaign-spring-2021-advertising-update

[5] There is little variability between samples, suggesting using the average is not a concern. The Google Trends website is https://trends.google.com.

[6] The denominator in Equation (2) includes Washington D.C. as Google Trends reports search values for Washington D.C. in addition to the 50 U.S. states. However, we could not obtain a precise search value for the Washington D.C. metropolitan market because it is included under several other markets, so we excluded it from our market-level sample but not the state ranking. We similarly include Alaska in the state rankings but exclude it from our market-level sample due to incomplete data.

[7] We exclude advisor assistants from our sample.

[8] Note that this is the average at the metropolitan market-level and it is not weighted by population. Therefore, our 10.1% estimate reported in Table 2 is a better metric for estimating overall representation within U.S. markets.

[9] In unreported results available upon request, the coefficient estimates and statistical significance for *animus* and *Black* remain the same as those reported in Table 4 when *GenAff* and *BlackAff* are not included.

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