Racial Retaliation and Updating:
Black Athletes and Racial Hate

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Abstract

This paper examines how racial animus responds to the presence and performance of minority star athletes, focusing on Black quarterbacks in the National Football League (NFL) – a highly salient media environment central to national and regional identity in the United States. We show that exposure to Black quarterbacks shapes racial hostility in both the short and long-run. Using a game-day event-study design, we identify evidence of emotion-driven racial retaliation. Relative to games where both quarterbacks were white, losses involving a Black quarterback are followed by a 16% increase in hate crime rates. These effects are concentrated after emotionally engaging games which generate a 40% rise in hate crimes, a 36% increase in hate speech indicators, and a 0.035 sd increase in implicit bias. In the long-run, we document a performance-contingent updating process. Areas with low-performing Black quarterback-led teams exhibit little change in racial animus. In contrast, when Black quarterback-led teams advance to championship games, hate crime rates fall by 32%, racial slur searches decline by -0.082 sds, hate speech indicators decrease by 17%, and implicit bias measures fall by -0.040 sds. Exposure to opposition Black quarterbacks does not produce long-run effects.

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1 Introduction

Racial prejudice and racial hate continue to be pervasive problems in the United States. Reported incidents of anti-Black hate crimes increased by 84% between 2014 and 2023. Hate speech has proliferated on social media platforms. Prejudicial attitudes and behaviors continue to cause discrimination in education, health, employment, housing, and the criminal justice system (Alesina and La Ferrara (2014), Bayer et al. (2017), Lang et al. (2005)). In jobs and schools, in-group tolerance continues to favor majority group members in the allocation of blame and punishment (Egan et al. (2022), Sarsons (2017), Skiba et al. (2002)).

Recognition that racial biases and prejudices carry important social and economic costs motivates an extensive literature that seeks to understand and reduce prejudice (Lang and Kahn-Lang Spitzer (2020), Rutland and Killen (2015), Paluck et al. (2021), Bertrand and Duflo (2017)). Though media representations (and under-representation) are often cited in public discourse as a mechanism that contributes to the perpetuation of racial prejudices, causal evidence examining the effects of exposure to celebrities and public-figures is limited. This is particularly true for star minority athletes. Sporting events are media saturated salient events central to national and regional identities. Teams often have racially diverse rosters of players, of varying ability, who carry the weight of fans' expectations into games where emotions can run very high. Though there is evidence that an exceptionally successful Muslim soccer star, Mohamed Salah, reduced anti-Muslim hate crimes and speech in Liverpool in 2017 (Marble et al. (2021)), our broader understanding of how minority athletes affect racial hate and attitudes is limited. How does racial animus respond to the presence of minority players right after games when emotions are running exceptionally high? Does the response depend on the game's outcome? Does facing an opposition minority player increase racial animus? Are effects different in the long-run, as people update their beliefs about minority athletes?

This paper begins to answer these questions and fill this gap. We examine how racial animus responds to the presence and performance of minority star athletes in team sports, namely Black quarterbacks in the National Football League (NFL). By examining responses to Black quarterbacks in American football NFL games, we provide new evidence on how star players in one of America's most visible cultural institutions can shape public attitudes and behavior toward minority groups around game days and over the course of a season.

First, using an event study design we investigate how racial animus changes in the very short-run – the five days surrounding games. We find evidence of a racial retaliation effect: racial animus increases when Black quarterbacks are perceived of as "blamable" for a negative outcome. By examining close scoring upset games that generate significant emotional responses, we find that relative to similar games where both quarterbacks were white, losses involving a Black quarterback are followed by a 40% increase in the anti-Black hate crime rate. In contrast, emotionally engaging wins involving Black quarterbacks leave hate crimes rates unchanged. This effect is observed on other measures of racial animus, including online hate speech indicators on reddit, which increases by 36%, and implicit racial bias which rise by 0.035 sds.

We also estimate the persistent effects of exposure to both local and opposition Black quarterbacks in the long-run. For local Black quarterbacks, we compare how outcomes evolve in areas with Black and white quarterback teams over the course of an NFL season. We find that Black quarterbacks on low performing teams have limited effects. In contrast, and consistent with Marble et al. (2021), sustained exposure to high-performing local Black quarterback teams leads to persistent reductions in racial hostility. In the months following the end of the NFL season, areas where Black-quarterback teams advance to the championships have hate crime rates that are 32% lower, Google searches for racial slurs decline by -0.082 sd, the share of reddit submissions moderated from team subreddits is 17% lower, and implicit racial biases drop by -0.040 sd. For opposition Black quarterbacks, we find no evidence that increased exposure to opposing Black quarterbacks – either through playing more games against Black quarterbacks or being knocked out of the playoffs by a Black-quarterback team – leads to persistent increases in racial animus.

Our work examining the impacts of media saturated sporting events contributes to the literature on mass media's economic impacts (DellaVigna and La Ferrara (2015)) and specifically on it's ability to impact prejudice. A growing body of work has shown that exposure to hostile messaging through film and radio can worsen inter-group biases and hate, and increase persecution (Yanagizawa-Drott (2014), Adena et al. (2015), Ang (2023)). The propagation of hate speech on social media has also been shown to impact hate crimes offline (Müller and Schwarz (2021), Müller and Schwarz (2023), Cao et al. (2023)). Whether media based contact with minority celebrity role-models can impact majority group prejudices – the parasocial contact hypothesis (Schiappa et al. (2005)) – has been less studied, a gap often noted in reviews of the contact theory and role-model literatures (Paluck et al. (2021), Kearney and Levine (2020), Bertrand and Duflo (2017)). Indeed, while a substantial literature in economics has examined the impact of minority representation in leadership and role model positions, the focus of this work has generally been on academic and aspirational outcomes, particularly for the minority group, be they female students in STEM fields or racial and ethnic minorities (Riley (2024), Gershenson et al. (2022), Lim and Meer (2020), Fairlie et al. (2014), Dee (2005)). Evidence of prejudice reduction due to media based contact with out-group role models is fairly limited (Paluck (2009), Blouin and Mukand (2019), Duquennois and Zeng (2025), Plant et al. (2009), Miller et al. (2020)). Particularly relevant to our study is Marble et al. (2021) who study the impact of the highly successful soccer star Mohamed Salah on anti-Muslim hate crimes and hate speech in Liverpool when he joined their club in 2017. Our findings are consistent with the effects they document but make several important contributions. First, we move beyond the study of a single famous successful individual. By comprehensively examining the impact of 68 Black quarterbacks over 23 NFL seasons we establish that their findings are a generalizable reaction to a minority identity rather than an idiosyncratic individual effect. Second, we examine the effect of playing against opposition minority players, allowing for a more complete picture of how minority athletes affect these outcomes not just in their team's region but in opposition teams' regions as well. Third, we examine how these impacts crucially depend on performance, finding a pattern of racial retaliation. Finally, we examine both the effects of persistent long-run exposure to minority players, as well as the emotion driven responses that happen right around games using multiple measures of racial animus that span both concrete criminal behavior (anti-Black hate crimes) and more latent, attitudinal expressions (online hate speech, racial slur internet searches, and implicit racial biases).

This paper also contributes to the literature examining the economic and social impacts of sporting events. Research has shown that sporting events generate powerful emotional shocks with important social consequences. Upset wins and losses of popular sports teams are known to impact domestic violence (Card and Dahl (2011), Matsuzawa and Arnesen (2024)) and other violent crimes such as assaults, vandalism, alcohol-related arrests and robberies (Rees and Schnepel (2009), Munyo and Rossi (2013), Montolio and Planells-Struse (2016), Ivandić et al. (2024)). Emotional reactions to games lead to harsher sentencing of juveniles in the following week (Eren and Mocan (2018)) and lower stock returns (Edmans et al. (2007)). Sporting events have even been shown to influence birth rates nine month later (Stoecker et al. (2016)) and increase the prevalence of low birth weights for in utero exposed infants (Duncan et al. (2017)). Our short-run results contribute to this literature by examining differences in short-run effects by quarterback race, showing that these sporting events trigger racialized emotional shocks characterized by retaliatory behaviors towards out-groups who share an identity with star athletes. We show that sporting events can impact identity based behaviors towards out-groups with important consequences. A couple existing papers have examined the impact of international sporting tournaments on national identity building. Depetris-Chauvin et al. (2020) show that international soccer tournaments strengthen national identities and reduce civil conflict, and Rosenzweig and Zhou (2021) document a similar effect, with a concurrent increase in negative views towards foreign refugees. Our work contributes to our understanding of the impacts of sports on co-national identities by showing that sports can impact attitudes towards minority groups, and thus social cohesion between groups within a country. Furthermore, most of this literature has focused on effects resulting from emotional shocks that occur right around game days. Our season level specification allows us to examine the longer-run effects of repeated exposure to a Black quarterback revealing sustained changes in behaviors.

The remainder of this paper is organized as follows. Section 2 presents contextual information on the NFL and Black quarterbacks in the NFL. Section 3 outlines a simple model. Section 4 presents our data. Section 5 focuses on our short-run analysis, presenting first our estimation strategy followed by our short-run results. Section 6 develops our season analysis beginning with the estimation strategy and then presenting results. Section 7 concludes.

2 The NFL and Black quarterbacks

The National Football League (NFL) is the highest level of professional American football and the most popular sporting league in the United States, receiving high levels of media attention. It is estimated that Super Bowl games, which determine the season's winning team, are watched by over 40% of the US population. Yet even regular season games are highly visible events averaging over 16 million viewers. The league is composed of 32 teams. The regular season, which typically runs from September to January, features weekly games. These often occur on Sundays (85% of games) though teams occasionally play on Mondays (7%), Thursdays (5%), and Saturdays (4%). The regular season consisted of 16 games until the 2021 season when it was increased to 17 games per season. During the regular season, games are determined by a scheduling formula. After the regular season, the best teams qualify for the playoffs (12 teams prior to the 2020 season and 14 teams thereafter). The playoffs, typically running throughout January, are a knockout tournament that leads to the "semi-final" conference championship games (4 teams), and finally to the Super Bowl, usually held in the first two weeks of February.

Games are highly structured, with frequent stops in play, highly specialized positions, and players who take the field only for offense or defense. Quarterbacks lead the team's offense and must make quick decisions under pressure—they receive the ball at the start of most plays and implement the team's play strategy. As a result, quarterbacks are often a team's most visible and influential player, receiving a substantial share of media attention, and the position is a symbol of leadership and masculinity in American culture. Though the NFL began reintegrating Black players in 1946, for decades Black athletes were largely excluded from the quarterback position due to racist stereotypes questioning their intelligence, leadership, and decision-making ability (Rhoden (2007), Reid (2022)). In 1953, Willie Thrower broke that barrier as the first Black quarterback to play in an NFL game, and in 1968, Marlin Briscoe became the first to start as quarterback in the modern era. Though Black athletes have long comprised the majority of NFL players, roughly 70% since 1990, the number of Black quarterbacks rose only gradually from the late 1970s onward (Marquez-Velarde et al. (2023)).[1] In our period of study, about 20% of quarterbacks were Black between 2002 and 2020 with a notable increase afterwards to reach 37% in 2024 (Figure 1). Almost all NFL players are American.

3 A model of Black athletes' impacts on racial animus

We generate a parsimonious model of how exposure to NFL Black quarterbacks impacts racial animus in a team's catchment area, focusing on the two mechanisms most consistent with our findings: emotion-driven racial retaliation in the short run and performance-dependent parasocial updating in the long run.

[1] Racial discrimination within professional sports has been studied fairly extensively. We know that racial biases have influenced referee and umpire calls (Price and Wolfers (2010), Parsons et al. (2011), Gallo et al. (2013)) and that the racist behavior of fans impacts player performance (Caselli et al. (2023), Caselli et al. (2024)). In the NFL, several studies have explored the effects of player race on careers and pay with mixed findings, reflecting the wide variety of seasons, positions, and approaches employed for analysis (most recently Berri et al. (2023), Gregory-Smith et al. (2023), Keefer and Kniesner (2023), Keefer (2013), Burnett and Van Scyoc (2015), Ducking et al. (2014) Ducking et al. (2017)). With respect to quarterbacks, it is widely acknowledged that the position was historically much less accessible to Black players. In more recent periods, some evidence suggests Black quarterbacks experience differential treatment in benching and pay (Volz (2017), Berri and Simmons (2009), Berri et al. (2023)).

Let areas contain a continuum of individuals, i, who, after their team n's game g in season s, choose to act upon their racial animus or not. The additional utility i receives from taking such an action after game g is

$$U_{ing} = \theta_{ins} + r_{ng} - c_{ins} + \varepsilon_{ig}, \tag{1}$$

where θ_{ins} captures i's baseline racial animus, r_{ng} captures the short-run differences in racial animus generated by game g for team n, c_{ins} is an individual-specific cost to the action, and ε_{ing} is an i.i.d. shock. In the short-run, changes in racial animus right around game day reflect changes in r_{ng}, as baseline racial animus and cost do not vary in the short-run. Longer run effects of season exposure to Black quarterbacks are captured by changes in θ_{ins}.

Short-run emotion driven racial retaliation (r_{ng}): We use the term racial retaliation to describe a process whereby members of a majority group direct racial animus toward innocent out-group bystanders when a salient out-group member is perceived as "blamable" for a negative outcome. Experimental evidence shows that, following negative outcomes, majority group members are more likely to attribute responsibility to minority individuals—even when those individuals are not causally responsible (Bursztyn et al. 2022; Bauer et al. 2023), a pattern often referred to as *racial scapegoating*. Racial retaliation differs from racial scapegoating in that it requires the negative outcome to be associated with a racially salient out-group figure who can plausibly be blamed. The hostility is then displaced onto the broader group.

We model games as generating affective responses – increasing in wins and decreasing in losses– that are more pronounced for emotionally engaging games such as close games with unexpected outcomes. The affect generated by game g for team n is

$$a_{ng} = (\gamma_0 + \gamma_1 Engaging_{ng}) \cdot (\alpha_1 Win_{ng} + \alpha_2 Loss_{ng}). \tag{2}$$

Affect shocks generate retaliatory racial animus when they are attributed to racially salient agents in the game like Black quarterbacks. We model this blame mapping as

$$r_{ng} = a_{ng} \cdot (\pi_l l_{ng} + \pi_o o_{ng}), \tag{3}$$

where $\pi_l, \pi_o \geq 0$ capture whether changes in affect are attributed to Black quarterbacks and generate retaliatory black animus towards local Black populations. Note that π_l and π_o allow for the magnitude of this effect to depend on whether the Black quarterback was playing for the local or opposition team.

Long-run performance dependent updating (θ_{ins}): Repeated exposure to Black quarterbacks – who occupy a highly visible and admired leadership position – may shift racial attitudes by altering beliefs about competence, leadership and social norms. Over time, such exposure might generate stereotype revision, norm updating, or changes in priors about group characteristics.

The parasocial contact hypothesis posits that repeated media exposure to positively portrayed out-group members can reduce prejudice (Schiappa et al. (2005)). While a generalized version of this hypothesis predicts declines in animus from repeated exposure to Black quarterbacks regardless of performance, a performance-mediated version allows for more nuanced, outcome-contingent effects: positive performance—especially by local quarterbacks—should produce larger reductions in animus by providing favorable signals. Evidence that anti-Muslim hate declined in Liverpool after the highly successful Mohamed Salah joined Liverpool FC (Marble et al. (2021)) is consistent with this mechanism. In contrast, poor performance may dampen positive updating or even reinforce negative priors, particularly in emotionally charged, media-saturated environments that amplify blame. Poor performances by minority athletes could therefore generate persistent racial backlash—a hypothesis that has not yet been empirically tested.

With these mechanisms in mind, the effects of exposure to opposition quarterbacks are theoretically ambiguous. Such exposure is less frequent and occurs in a markedly different context than exposure to local players. Although opposition minority athletes may increase the salience of minority leadership, media portrayals are less likely to be positive, and the competitive setting lacks a shared local identity. This context may heighten social boundaries and reinforce group distinctions rather than attenuate them. Consequently, the long-run effects of opposition exposure depend on how performance signals interact with identity and attribution processes—an empirical question that remains unexamined.

Accordingly, we flexibly model baseline racial animus, θ_{ins}, as a slow-moving state variable that evolves through repeated exposure to Black quarterbacks and their team's performance, with effects that can differ for local and opposing Black quarterbacks. Attitudes update as individuals partially adjust their existing attitudes toward a season-specific signal observed for team n during season s. The change over the course of the season is given by

$$\theta_{in,s+1} - \theta_{ins} = \lambda_L \left(\tilde{\theta}^L_{ns} - \theta_{ins} \right) + \lambda_O \left(\tilde{\theta}^O_{ns} - \theta_{ins} \right) + \varepsilon_{ins}, \tag{4}$$

with

$$\tilde{\theta}^L_{ns}(L_{ns}, Rec_{ns}), \qquad \tilde{\theta}^O_{ns}(O_{ns}, \Phi_{ns}), \qquad \lambda_L, \lambda_O \in (0,1). \tag{5}$$

λ_L and λ_O govern the rate of updating while $\tilde{\theta}^L_{ns}$ and $\tilde{\theta}^O_{ns}$ summarize the cumulative effect of exposure to local and opposition Black quarterbacks during the season. The first exposure measure, $\tilde{\theta}^L_{ns}$, is a function of exposure to a local Black quarterback, L_{ns}, and the team's performance record, Rec_{ns}. The second exposure measure, $\tilde{\theta}^O_{ns}$, captures exposure to Black quarterbacks on opposing teams, O_{ns}, and the outcome of these interactions, Φ_{ns}. ε_{ins} captures idiosyncratic shocks to animus unrelated to football exposure.

4 Data

4.1 Measuring exposure to Black quarterbacks

To measure exposure to Black quarterbacks, we proceed in two steps. First, we delineate each NFL team's geographic catchment area. Second, using play-by-play game data, we identify games and seasons where a Black quarterback served as the team's primary quarterback.

Defining NFL teams' geographic catchment areas: We match U.S. Designated Market Areas (DMAs), which delimitate local media markets, to NFL teams by estimating DMAs' ratings for each of the 32 NFL teams. For each DMA-team combination we calculate

$$\widehat{Ratings}^{team}_{DMA} = HomeRatings^{team} \times GoogleSearches^{team}_{DMA}.$$

$HomeRatings^{team}$ is an estimate of a team's ratings in the team's local DMA.[2] $SearchIndex^{team}_{DMA}$ is built using Google trends indexes of DMA searches for each team over the 2004-2025 time period.[3]

[2]Disaggregated ratings data is not easily available. To estimate this we take the average of the team's ratings in teams' local media markets as reported for five available seasons (2011, 2012, 2013, 2020, 2021) in the Sports Business Journal (Karp (2014); Ourand (2022)).

[3]The Google trends indexes we use are requisitions of DMA level Google trends indexes for each team over the 2004-2025 time period. These are set to 1 for the DMA with the greatest interest in the team over the 2004-2025 period

DMAs are then matched to their highest rated team. NFL team catchment areas thus defined are mapped in Figure 2.

NFL data: Using public APIs, we collect play-by-play NFL data for every game in the 2002 thru 2024 seasons. In this data we observe every action players took on the field during the game. Though only one quarterback can be on the field at once, teams can field multiple quarterbacks over the course of a game if their starting (main) quarterback is injured or is otherwise removed from play. We define a team-game's lead quarterback as the quarterback with the greatest share of plays during the game. The race of the quarterbacks is then identified by a team of research assistants. For our season level analysis, we define team-seasons as having a Black quarterback if the majority of the team's regular season games are defined as having a Black quarterback.

Overall, this data covers 6214 games and 736 season-teams.[4] Of these, we omit from our analysis 345 games and 23 season-teams where the main quarterbacks is one of the two non-Black Hispanics or two Samoan quarterbacks in our data, giving us a sample composed of European-American and African-American quarterbacks. For our short run estimations, which examine outcomes in 5 day windows centered around game days, we further restrict our analysis to team-games that occur at least 7 days after the team's previous game and 3 days before the subsequent game. Finally, for brevity and clarity of exposition, our game-level analysis also omits 307 games that feature two Black quarterbacks as these are few in number and confound multiple effects, complicating interpretation. With these restrictions, our final game-level data covers 5562 games. Of these, 3501 are classified as having two white quarterbacks, while 2061 have a Black quarterback on the field. At the season level, 152 of 713 season-teams are classified as having a Black quarterback.

with the index for other DMAs interpretable as searches relative to the top searching DMA. Google trends requisitions are calculated using a sample of Google searches (rather than the universe of Google searches that were conducted during a period), with the sample changing on a regular basis. To ensure that we generate a consistent search index measure, we collect 8 separate requisitions and calculate a team's search index measure as the mean index across these 8 requisitions. To verify that our measure is stable, we correlate this with the average calculated with only the first 7 requisitions finding a correlation of 1.00.

[4]Each of the 32 teams played 16 regular season games between 2002 and 2020, and 17 between 2021 and 2024. Playoffs consisted of 11 games between 2002 and 2019 and 13 games between 2020 and 2024. We drop the 2022 week 17 game between the Buffalo Bills and the Cincinnati Bengals that was canceled early in the first quarter due to Bills player Damar Hamlin's medical emergency.

4.2 Measures of racial attitudes and hate

Anti-Black hate crimes: We use the FBI's Uniform Crime Reporting Hate Crime Statistics for 2002–2025.[5] These data are the most comprehensive standardized police-reported measure of hate-crime incidents available in the United States and are widely used in hate-crime research (Müller and Schwarz 2023; Anderson et al. 2020; Mulholland 2013). Nevertheless, it is important to note that reported incidents documented in these data are only a small share of all hate crimes. Many hate crimes are never reported to law enforcement, and many local law enforcement agencies do not reliably report hate crimes to the FBI as reporting is voluntary (Dharmapala and Huq (2024)).[6] The incident-level files report the calendar date and location of each incident, a bias-motivation category identifying the targeted group, and the reporting agency. We map incidents to counties using the locations of over 24,000 reporting agencies. We then calculate the count of anti-Black incidents on each day for each DMA to generate the daily DMA incident rate (per 10 million). For our season level analysis, day counts are aggregated to generate monthly DMA incident rates (per 100,000). Throughout, we check that our main findings are robustness to alternative measurement and specifications of hate crimes.[7] After matching this data with NFL games, our final sample spans the 2002 to 2024 seasons covering 10257 unique games-teams and 713 unique season-teams.

Reddit data: We collect reddit submissions from 2010 to 2024.[8] Our sample is composed of 32 subreddits dedicated to discussion of the 32 NFL teams. For each subreddit-day we calculate the daily count of submissions to the subreddit. [9] We then calculate the share of submissions that were removed by content moderators as our first indicator of hate speech.[10] For the submissions

[5] In this data, a hate crime is defined as a criminal offense motivated, in whole or in part, by the offender's bias against a protected characteristic such as race.

[6] Between 2011 and 2015, 54 percent of hate crimes identified in the National Crime Victimization Survey were not reported to the police (Dharmapala and Huq (2024)).

[7] These include an extensive indicator specification, a zero adjusted log specification, linear and Poisson specifications on incident counts and the inclusion of population weights.

[8] We use reddit data from 2010 onward for the following reasons. First, prior to 2010, reddit's overall activity was low and many subreddits either did not exist or were nascent, which would induce severe left-truncation and compositional shifts across units. Second, HATEBERTA was developed and tuned on 2010s social-media text; beginning in 2010 mitigates distribution shift between the training corpora and our corpus.

[9] We focus on Reddit submissions rather than comments for several reasons. First and foremost, comments associated with submissions that were moderated off of the platform are unobserved resulting in a selected sample at the comment level. Second, submissions are more likely to reflect deliberate and sustained expression, whereas comments frequently capture rapid reactions and conversational back-and-forth, often consisting of exclamations or fragmentary expressions with limited semantic information. This substantially increases measurement error when estimating hate-speech intensity using text-based classifiers.

[10] Reddit historically relied on decentralized, volunteer-based moderation and imposed few platform-wide restrictions prior to 2015. From 2015, reddit began banning prominent subreddits associated with harassment and hateful content, eventually introducing an explicit platform wide hate-speech policy in 2020 (Reddit 2020; Chandrasekharan et al. 2017).

with visible content, that were not removed by moderators or deleted by authors, we generate a measure of anti-Black hate speech. We use **HATEBERTA**, a transformer-based classifier trained for abusive-content detection on reddit (Caselli et al. 2020).[11] To obtain a measure of anti-Black targeted hate-speech, we further fine-tune **HATEBERTA** using **ToxiGen** (Hartvigsen et al. (2022)) to generate a 0 to 1 score interpretable as the probability the text contains anti-Black targeted hate-speech. Using this measure, we find minimal amounts of anti-Black hate speech in the submissions to official NFL team subreddits that were not removed by moderators. The ToxiGen estimated probability that a submission contains anti-Black hate is 0.019% on average and only 0.04 % of submissions have an estimated probability greater than 0. Accordingly, we treat the moderation share as our primary indicator of hate speech activity. Estimates using the ToxiGen score are imprecise and reported in the appendix. After matching the reddit data with NFL games, our final sample spans the 2009 to 2024 seasons, covering 5765 unique game-teams and 429 season-teams.

Racial Animosity Index (RAI) using Google search indices: We construct a location and time varying measure of anti-Black racial animus using the index of Google searches for racial slur queries.[12] This measure, first developed by Stephens-Davidowitz (2014), has been widely used in the literature as a measure of racial animosity (Chetty et al. (2020), Kline et al. (2022), Derenoncourt (2022)). The slur query is most frequently searched for along side the term "joke(s)" which returns offensive websites. Searches that include the slur query are not uncommon. From 2004-2025, such searches are about as common as searches for the terms "cavity+cavities".

To capture geographic and temporal variation in slur searches, while still maintaining sufficient search volumes for index construction, we construct the standardized index for DMAs in two-month time bins using the mean index calculated across ten requisitions from Google trends.[13]

In addition to these platform-wide policies, NFL team subreddits enforce their own community-specific content rules, which commonly prohibit hate speech and harassment, as well as other nuisance content such as spam, off-topic discussions, and cross-posting.

[11] **HATEBERTA** is trained on a broad spectrum of hate speech categories, including those targeting racial and ethnic groups (e.g., Black, Asian, Latino).

[12] Specifically, we requisition indexes for searches that include the terms "n___ +n___s" — henceforth "the slur query."

[13] For each requisition, the Google index is set to 1 for the DMA with the greatest share of slur queries while the index for other DMAs are interpretable as search intensity relative to the top searching DMA. Google trends requisitions are calculated using a sample of google searches (rather than the universe of Google searches that were conducted during a period), with the sample changing on a regular basis. To ensure that we generate a consistent measure, we collect ten requisitions for every two-month bin and calculate the mean across these ten requisitions. As Google does not return an index when samples are too small, we drop any mean calculated with fewer than two observed requisitions (25.4% of DMA-2month bins, mostly in the earliest years of the data and low population DMAs). We then calculate the mean index across these ten requisitions which is then standardized.

After matching this index with NFL seasons, our final sample spans the 2004 to 2023 seasons, covering 613 team-seasons.

Implicit association test (IAT) scores: Measures of implicit biases come from the publicly available data on implicit association tests collected online by *Project Implicit*. *Project Implicit* allows interested parties to take a short survey and implicit association tests (IATs) generating a measure of their implicit associations with individual characteristics such as race. IATs are widely used in psychology, and increasingly in economics, as a way of measuring implicit attitudes (Glover et al. (2017), Carlana (2019), Corno et al. (2022), Lowes et al. (2015)).[14] After matching the IAT survey data with NFL games, our final sample spans the seasons from 2002 to 2024, covering 9660 unique game-teams and 713 season-teams.

Table 1 provides descriptive statistics for our main outcomes measured at both the day (panel (a)) and season (panel (b)) levels.

5 Game-day Responses: Racial Retaliation

In this section, we begin by examining the impacts of exposure to Black quarterbacks on and after game days. Previous work has shown the importance of powerful emotional responses to game outcomes in the days that follow games (Card and Dahl 2011; Montolio and Planells-Struse 2016; Ivandić et al. 2024; Matsuzawa and Arnesen 2024). We find that beyond simple emotional reactions to wins and losses, we observe evidence of a racial retaliation effect. Racial animus increases after lost games when the game featured a Black quarterback, regardless of whether they were playing for the local or opposition team. This racial retaliation effect is driven by engaging emotional close-upset games, consistent with findings in Card and Dahl (2011) and Matsuzawa and Arnesen (2024) that show how such games fuel emotion driven responses. Below we explain our game day

[14]When completing the race IAT, respondents are sequentially presented with images of Black and white individuals, and words that have positive or negative connotations. Respondents complete a series of rapid sorting exercises grouping together the images with words. The IAT is meant to measure the strength of a respondent's association between individual characteristics and word connotations, as sorting is easier when associated items are sorted together. IAT measures have been the subject of increased scrutiny in the psychology literature (Ratliff and Smith (2021)). There is generally agreement that these measures are relevant and predictive, particularly for socially sensitive topics (Greenwald et al. (2009), Bertrand and Duflo (2017)), and aggregate regional measures (Hehman et al. (2019)). Disagreements have centered on the validity of the *implicit* bias construct, if it differs from *explicit* biases, and whether the low test-retest reliability is due to high measurement error, or the construct itself being time variant (Gawronski (2019), Schimmack (2021), Connor and Evers (2020)).

empirical strategy and present these findings.

5.1 Game-day empirical strategy

Our game-day design estimates how outcomes in the days that immediately follow a game change based on the racial composition of the quarterbacks that played, the game's result, and expectations. Using the NFL game data and the data collected on player race, we classify game g for NFL team n as having a Black quarterback ($QBBlack_{ng} = 1$) if a Black player played that position for the majority of the games' plays. For each game-team we then define C, the game's quarterback composition (QBc_{gn}) from each team's perspective. For our main specification, we examine two different quarterback compositions: $w = 1$ games where both quarterbacks are white (eg. white-white games) and $b = 1$ games where any quarterback (opposition or local) is Black. Heterogeneity between these is examined subsequently. For each of these compositions, we examine how outcomes change in five day windows centered around game days ($d = 0$). We use a pre-post specification where $Post_{dg}$ is set to 1 for the game day and the two subsequent days, and 0 for the two days prior. $Post_{dg}$ is interacted with our indicators for the game's quarterback composition and whether the game was won ($Win_{gn} \in \{0, 1\}$).[15] We estimate

$$\begin{aligned} Y_{agnd} =& \rho_0 + \rho_1^w Post_{dg} + \rho_2^b Post_{dg} \times \mathbb{1}\{QBc_{gn} = b\} \\ &+ \rho_3^w Post_{dg} \times Win_{gn} + \rho_4^b Post_{dg} \times \mathbb{1}\{QBc_{gn} = b\} \times Win_{gn} \\ &+ \eta_{ag} + \omega_d + \epsilon_i, \end{aligned} \tag{6}$$

where Y_{angd} is an outcome for area a, team n, on day d, around game g. A day of the week fixed effect, ω_d, controls for weekly trends in outcomes. Importantly, we include a $area \times game$ fixed effect, η_{ag}, which restricts our estimating variation to outcomes measured around the same game for the same geographical unit (and thus the same team). This fixed effect absorbs baseline racial animus, as well as any cost associated with the expression of racial animus, which we treat as fixed in the short-run.

ρ_2^b in equation 6 identifies how the change in outcomes after games differs for lost games involving a Black quarterback, as compared to white-white quarterback losses. ($\rho_2^b + \rho_4^b$) gives this differential for wins. As racial retaliation is a response to the affect shock generated by the game, we estimate these effects separately for emotionally engaging and unengaging games. We

[15] Ties are uncommon in the NFL during this period. In our game data, only 14 of 6214 games resulted in a tie. These are coded as $Win_{gn} = 0$.

use close-upsets games to identify emotionally engaging games. These are close scoring games where the final score differential is 7 or less (i.e. one touchdown determined the games outcome), that are also upset games in that the pre-game spread predicted that the loosing team would win by 3 points or more. Unengaging games are those that are neither close scoring nor upsets.

For figures we estimate equivalent event time specifications where coefficients are calculated for each day relative to the day before the game.

5.2 Short-run effects of Black quarterbacks

Anti-Black hate crimes: Table 2, rows 3 and 4, reports our main short-run estimates for local Black quarterback games on DMAs' daily hate crime incident rates (per 10 million). We find that hate crimes increase after losses involving a Black quarterback due to these games activating an emotion driven racial retaliation effect.

Column 1 reports estimates of equation 6 on all games in our analysis sample. On average, we find that the hate crime rate differentially increases by 0.030 (p-value=0.017), a 16% increase, after losses involving a Black quarterback as compared to the change observed after losses where both quarterbacks were white (which do not significantly impact hate crimes – per row 1). Following wins, the differential increase in the hate crime rate, $(\rho_2^b + \rho_4^b)$, is much smaller at 0.012, and we cannot reject the null of no effect (p-value=0.31).

This pattern is driven by emotionally engaging games. We follow the literature and examine the effects around games that generate significant emotional engagement and shock. Column 2 estimates equation 6 on close-upset games finding much larger effects. After a close-upset loss involving a Black quarterback, the hate crime rate differentially increases by 0.075 (p-value=0.018), a 40% increase. In contrast, the $(\rho_2^b + \rho_4^b)$ point estimate of -0.032 suggests a reduction in the hate crime rate following wins involving Black quarterbacks, though this is not statistically significant (p-value=0.34). The first two panels of Figure 3 present event day estimates for these close-upset games. For reference, panel (b) plots event day estimates for white-white emotionally engaging losses (ρ_1^w) and emotionally engaging wins $(\rho_1^w + \rho_3^w)$. Panel (a) plots the differential effects for emotionally engaging losses (ρ_2^b) and wins $(\rho_2^b + \rho_4^b)$ involving Black quarterbacks. Consistent with the aggregated estimates reported in the table, panel (b) shows no evidence of any impact around white-white games while panel (a) shows large differential effects that begin on game day and persist for the next two days.

The emotional engagement these games create is key to generating these effects. In columns 3 and 4 we split the sample between games that may generate some level of emotional engagement, having either a close score and/or an upset outcome (column 3), and unengaging games that are neither close scoring nor upsets (column 4). Though the point estimate for losses in unengaging games is positive, it is small and not statistically significant at 0.012 (p-value=0.53). These patterns of large increases after emotionally engaging losses involving Black quarterbacks with little to no change following other games, be they wins or unengaging games, are robust to alternative specifications of our measure of hate crimes and alternative combinations of fixed effects (see appendix tables A1 and A2). They are also observed in our other measures of racial animus.

In appendix Table A3 we examine impacts on hate crimes targeting white, Hispanic and other racial groups. Consistent with a retaliation mechanism, we find no evidence of game-day changes in hate crimes targeting White or other racial groups. Hate crimes targeting Hispanics are less common. They do exhibit patterns similar to those directed at Black populations, although the effects are somewhat smaller in magnitude. It is worth noting that Hispanics encompass a racially heterogeneous population, including individuals with darker skin tones, some of whom also identify as Black.

Hate speech and IAT scores: Table 3 repeats the same analysis on the two other measures of racial animus that are observable at the day level: the share of submissions moderated off of NFL team subreddits, and white IAT scores. For both these outcomes, we see strikingly similar patterns: differential increases following close-upset losses involving Black quarterbacks (row 3 of columns 2 and 6), and little to no differential effect following wins, or after unengaging games.

For submission removals, we find that the share of submissions being moderated off of reddit experiences a general increases after all games (rows 1 and 2). This increase is substantially greater following emotional losses involving Black quarterbacks. The share of submissions being removed differentially increases by 0.046 (p-value=0.008), a 36% increase, after emotional losses involving a Black quarterback as compared to the change observed after such losses where both quarterbacks were white. Event day estimates for these close-upset games are illustrated in the second two panels of Figure 3. Panel (d) shows the general increase in moderation share around game days while panel (c) shows the large differential increase in the days following losses involving Black quarterbacks. We see no evidence of a differential change following engaging wins (0.008; p-value=0.60) or around unengaging games (column 4). Appendix Table A4 and Figure A1 examine whether the number of submissions is differentially affected by quarterback race. As expected, submission activity on team subreddits increases after games but we find no evidence of a differential effect around Black quarterback games.

Estimates on white respondents' IAT test scores are slightly underpowered but show a similar pattern. IAT scores differentially increase by 0.035 sds (p-value=0.08) after emotionally engaging losses involving a Black quarterback. We see no statistically significant evidence of a differential change following engaging wins (-0.020 sds; p-value=0.36) or around unengaging games (column 8). Event day estimates for close-upset games are illustrated in the last two panels of Figure 3. As anyone can log onto the *Project Implicit* website and take an IAT test, in appendix Table A4 and Figure A1 we examine whether the number of test takers around these games is differentially affected by quarterback race. We see no evidence that the number of IAT test takers changes around game day.

The asymmetric response to Black quarterbacks – heightened animus after emotionally engaging losses but not after wins – is most consistent with these games triggering a short-run racial retaliation mechanism. To further confirm this, we estimate equation 6 disaggregating our analysis to separately examine the effects of local ($C = l$) and opposition ($C = o$) Black quarterbacks. Estimates are reported in Table 4. Across all three outcomes we observe similar patterns. Racial animus indicators increase following engaging losses but not after engaging wins involving Black quarterbacks, regardless of whether the Black quarterback is playing for the local or opposition team. Though there are some differences in the point estimate magnitudes for local (ρ_2^l) and opposition (ρ_2^o) Black quarterbacks, all the ρ_2 estimates are positive. For all three outcomes, we fail to reject that ρ_2^l and ρ_2^o are equal. Similarly, all the corresponding ρ_4 estimates are negative, suggesting offsetting effects following wins. For all three outcomes, we fail to reject that $\rho_2^l + \rho_4^l = \rho_2^o + \rho_4^o$. Overall, there is no clear evidence of effect heterogeneity based on wether the Black quarterback is playing for the local or opposition team. This is consistent with a racial retaliation effect where either the local or opposition Black quarterback is "blamable" for the the negative affect shock.

While our findings provide evidence of short-run emotion-driven racial retaliation, other mechanisms may also operate in this setting. For example, the presence of Black quarterbacks in historically white, high-status positions could trigger a status threat mechanism, whereby members of dominant groups respond with increased out-group animosity when their relative position is perceived as challenged (Blumer (1958), Blalock et al. (1967)). Status threat would predict increases in animus following exposure to Black quarterbacks, particularly after wins over white quarterbacks. However, this pattern does not align with our estimates in Table 4 showing that animus rises following losses by local Black quarterbacks – a pattern consistent with affective retaliation but not status-based backlash. More broadly, multiple mechanisms may act simultaneously. While we cannot definitively rule out alternative processes, the empirical patterns we observe are most consistent with a pattern of short-run emotion-driven racial retaliation. Other mechanisms may contribute at the margin, but this mechanism is necessary to account for the observed results.

6 Season responses: Performance sensitive updating

The patterns described in section 5 show a racialized emotional response to the performance of Black quarterbacks by comparing outcomes for the same location in the days right around game days through the use of location-game fixed effects. While effective at isolating immediate short run responses, the use of these fixed effects absorbs any long term effects that repeated exposure to Black quarterbacks could generate. Marble et al. (2021) show evidence of reduced anti-Muslim attitudes for a year following Mohamed Salah's move to Liverpool in 2017. In this section we build on these finding in three important ways. First, we examine whether this long term pattern is generalizable, estimating it for a different sport and examining a large group of Black quarterbacks, helping to alleviate concerns about idiosyncratic effects tied to a single individual. Second, we examine how this pattern responds to performance. And third, we examine whether fan bases of teams that confront these players as opponents display any evidence of changed behavior as a result in the long-run.

Consistent with the findings in Marble et al. (2021), we observe reductions in anti-Black attitudes and hate in locations with Black quarterbacks on high performing NFL teams that make it to the conference championships (4 teams per season). In contrast, Black quarterbacks on low performing teams have limited effects. With respect to opposition Black quarterbacks, we find no evidence that playing against Black quarterbacks has any long-run effects on racial animus. Below we explain our estimating strategies and present these results.

6.1 Local Black quarterbacks in the long-run

6.1.1 Empirical strategy

Our long-run design estimates how the evolution of outcomes over the NFL season differs based on quarterback race and team performance. For the time period under consideration, the NFL regular season begins in early September and ends in early January. This is followed by playoff games in January, culminating in the Super Bowl which generally occurs in the first or second week of February. We define seasons as running from May to April so as to include measures of our outcomes both before and after NFL games are taking place. For tables, we divide seasons into three time periods T such that $T \in \{b, d, a\}$. We set our omitted period to b, the period before the season start (May thru August) which we compare to d, outcomes observed during the NFL season (September thru February); and a the after season (March and April) – our period of interest to observe persistent impacts. For figures, to better observe the evolution of outcomes over the course of the season, we divide seasons into six two-month bins, with $T \in \{mj, ja, so, nd, jf, ma\}$, omitting the July-August bin. We define a team n in season s as having a Black quarterback ($L_{ns} = 1$) if the majority of the team's regular season games are classified as being played by a Black quarterback. Finally, a team's season record (Rec_{ns}) is categorized into three levels R such that $R_{ns} \in \{r, p, c\}$. These are: r, our omitted category, for the 450 team-seasons who only played in the regular season, p for the 194 team-seasons that advance to the playoffs but not the championships, and c for the 92 team-seasons that advance to the championships. Our main specification estimates the differential effect of having a Black quarterback as compared to a white quarterback for teams with different season records as follows:

$$\begin{aligned} Y_{ansm} = \mu_0 + \sum_T \mu_T^r \mathbb{1}\{m = T\} \times L_{ns} + \sum_T \sum_{R \neq r} \mu_T^R \mathbb{1}\{m = T\} \times L_{ns} \times \mathbb{1}\{Rec_{ns} = R\} \\ + \tau_{as} + \kappa_{am} + \psi_{Rm} + \phi_{ms} + \epsilon_i. \end{aligned} \tag{7}$$

Y_{ansm} is an outcome for area a, team n, observed in month m, and season s. We include four main fixed effects. Because we are analyzing many years of data, the $area \times season$ fixed effect, τ_{as}, controls for the general evolution of the outcomes in area a over the years. The $month \times area$ fixed effect, κ_{am}, controls for seasonal variation in the outcomes that is specific to area a, and the $month \times record$ fixed effect, ψ_{Rm}, absorbs variation in the outcomes across the season attributable to the NFL team record, regardless of the quarterback's race. Finally, a $month \times season$ fixed effect,

ϕ_{ms}, controls for changes in outcomes that are common to all areas at a particular point in time. With this set of fixed effects, the $\hat{\mu}$'s estimate the difference in how our outcomes change over the NFL season in locations with Black quarterbacks as compared to those with white quarterbacks for teams performing at the same level.

One may be concerned that the race of a team's quarterback is not randomly assigned. It is plausible that teams in areas with more racial animus are less likely to select a Black quarterback. With these specifications, if teams make this choice in response to the level of racial animus in their fan base, the $area \times season$ fixed effect controls for this selection as we are estimating within season changes. Of greater concern is if teams select Black quarterbacks when racial hate in their fan base is trending downward. This could affect our within season estimates, generating downward bias over the course of a season. In Table A5 we check for evidence of this type of selection pattern. Having a Black quarterback in season s is regressed on $Std(HateCrimeRate_{n,s-1} - HateCrimeRate_{n,s-2})$, the standardized change in the hate crime rate in the team's catchment areas over the two prior seasons. Several specifications are tested. We find no evidence that reductions in hate crimes over the prior two seasons is predictive of a team having a Black quarterback.

6.1.2 Long-run effects of local Black quarterbacks

Anti-Black hate crimes: Table 5, column 1, reports the after season estimates from equation 7 on monthly DMA anti-Black hate crimes per 100,000. We find that areas with Black quarterback teams that make it to the NFL championships experience a differentially greater reduction in the hate crime rate over the course of the NFL season as compared to areas with championship level white quarterback teams. For non-playoff Black quarterback teams, the small and statistically insignificant estimates reported in the the first row implies that there is no significant or persistent difference in the hate crime rates experienced by areas with Black and white quarterbacks that do not make it to the NFL playoffs. In contrast, areas with championship level Black quarterback teams experience a substantial reduction in the hate crime rate relative to championship white quarterback team areas. Figure 4(a) shows the evolution of the differential gap between Black and white quarterback teams for championship teams (in red) and non-playoff teams (in blue). The black line shows the average differential across all performance records. Over the course of the summer, relative hate crimes levels across these comparison groups are stable. Consistent with a response to team quarterbacks, it is only with the September start of the NFL season that the hate crime rate in championship level team areas begins to drop, persisting though the NFL season and into the spring after the season's end. In the months after the season, their hate crime rate is differentially lower by (-0.016; p-value=0.052), a 32% decrease.

Alternative specifications of our hate crime measure (appendix Table A6) also estimate small reductions in hate crimes for non-playoff teams and large statistically significant reductions for championship record teams. This pattern is also robust to alternative estimation approaches using different combinations of fixed effects (appendix Table A7). We find no evidence of impacts on hate crimes targeting Whites, Hispanics, or other racial groups (appendix Table A8).

Google searches for racial slurs: Table 5, column 2, row 1, and the blue line in Figure 4(b) show that when a team led by a Black quarterback fails to make the playoffs, racial slur searches increase and remain high beyond the end of the NFL season. Relative to similarly performing teams led by white quarterbacks, racial slur searches in the subsequent after season are 0.059 standard deviations (p-value = 0.046) higher in areas where a Black quarterback team did not reach the playoffs. In contrast, as shown by the red line on Figure 4(b) and the last row of Table 5, column 2, racial slur searches display a persistent decrease for championship record teams led by Black quarterbacks. Relative to areas with similarly performing teams led by white quarterbacks, racial slur searches in the subsequent season are -0.082 standard deviations (p-value = 0.08) lower in areas with championship level Black quarterback teams.

Hate speech on reddit: Table 5, column 3, reports estimates on the share of submissions removed. These estimates lack statistical precision but generally follow a similar pattern consistent with a persistent reduction in racial animus associated with championship level Black quarterback teams. Figure 4(c) plots the two-month estimates of this differential for non-playoff (in blue) and championship level teams (in red), with the average for all teams plotted in black. We see no difference in the share of submissions removed for non-playoff Black quarterback teams as compared to non-playoff white quarterback teams. In contrast, at the championship level, the share of submissions removed is lower by -0.013 (p-value=0.21), a 17% reduction, for Black quarterback teams.

Implicit racial biases: Table 5, column 4, reports estimates on the Implicit Association Test scores of white test takers. We see no statistically significant differential changes in the IAT scores of areas with non-playoff Black quarterback teams. In contrast, teams led by a Black quarterback that reach the championship games experience a gradual decline in implicit racial biases starting in the playoff season (Figure 4(d)), reaching a reduction of -0.040 sd (p-value=0.002) that persists into the months after the end of the NFL season. Appendix Table A9 and Figure A2 examine whether exposure to Black quarterbacks might impact selection into taking an IAT test. We cannot reject the null of no differential effect on the number of IAT test takers for those exposed to championship level Black quarterback teams.

Taken together, our estimates across several different indicators of racial animus consistently suggest that in the long run, racial animus is affected by exposure to local Black quarterbacks. High performing championship level teams with Black quarterbacks lead to reductions in measures of racial animosity across a range of measures, implying that (i) local Black quarterbacks do induce racial attitudes do update, so $\lambda_L \neq 0$, and (ii) exposure to Black quarterbacks on high performing teams generate an animus reducing signal ($E[\tilde{\theta}^L_{ns}(L_{ns}=1, Rec_{ns}=C) - \theta_{ins}] < 0$). In contrast, the long-run effects of exposure to Black quarterbacks on low performing teams that do not advance to the playoffs are generally null, with the exception of a 0.059 sd increases in google searches of racial slurs. Taken together, the presence of Black quarterbacks on these low performing teams has either a null effect or may generate a small animus increasing signal ($E[\tilde{\theta}^L_{ns}(L_{ns}=1, Rec_{ns}=R) - \theta_{ins}] \geq 0$).

6.2 Opposition Black quarterbacks in the long-run

6.2.1 Empirical strategy

To estimate how the evolution of outcomes over the NFL season differs based on exposure to opposition Black quarterbacks we adapt the strategy developed in section 6.1. We use the same T time periods and the same $area \times season$, $month \times area$, $month \times record$, and $month \times season$ fixed effects to control for the general evolution of the outcomes over the years, area specific seasonal variation, seasonal variation attributable to NFL team performance and general time trends. Focusing on teams with white quarterbacks, we estimate

$$Y_{ansm} = \delta_0^E + \sum_T \delta_{1T}^E \mathbb{1}\{m = T\} \times E_{ns} + \tau_{as} + \kappa_{as} + \psi_{Rm} + \phi_{ms} + \epsilon_i, \tag{8}$$

where E_{ns} is a measure of exposure to opposition Black quarterbacks. We examine several different measures of exposure. For the first, we calculate G_{ns}, the number of regular season games team n

played against an opposition Black quarterback in season s. With this approach, the δ_{1T}^{G}'s estimate the effect of one additional regular season game against an opposition Black quarterback on the outcome in period T. We also estimate a specification disaggregating G_{ns} into wins and losses against opposing Black quarterbacks. Finally, because the average effect of a single game played against an opposition Black quarterback may not generate persistent impacts, our second approach focuses on the effect of games that may be particularly salient. Focusing on the subset of teams that were in the playoffs, we generate an indicator K_{ns} which is set to one for teams who were knocked out of the playoffs by a Black quarterback. With this approach, the δ_{1T}^{K}'s estimate the effect of being knocked out of the playoffs by an opposition Black quarterback on the outcome in period T.

6.2.2 Long-run effects of opposition Black quarterbacks

One team's local Black quarterback is, by definition, an opposition Black quarterback to a different team. In section 6.1 we identified that championship level local Black quarterbacks generated a long-run reduction in racial animus in their teams' catchment areas. In aggregate, the long-run effects of Black quarterbacks could be quite different if this reduction was offset by persistent increases in racial animus in opposing teams' catchment areas. Table 6 and Figure 5 examine this question using several approaches to categorize exposure to opposition Black quarterbacks. Focusing on teams with white quarterbacks, panel (a) of Table 6 reports the long-run effect of playing an additional regular season game against a Black quarterback, the δ_{1T}^{G}'s from equation 8 estimated with G_{ns}. Panel (b) of Table 6 and the left column of Figure 5 report these estimates, differentiating between wins and losses against opposition Black quarterbacks. Finally, panel (c) of Table 6, and the right column of Figure 5 report the long-run effect of being knocked out of the playoffs by an opposition Black quarterback, the δ_{1T}^{K}'s from equation 8 estimated with K_{ns}.

Using these approaches, we find no evidence that facing opposing Black quarterbacks on the field leads to persistent increases in racial animus. Estimated coefficients for regular season games in panel (a) and (b) are small in magnitude, while estimates in panel (c) lack statistical precision. None of the coefficients are statistically significant at the 95% level and we find inconsistent signs across our different indicators and for alternative measures of hate crimes (appendix Table A10). Overall, we find no solid evidence that playing against opposing Black quarterbacks increases racial animus. This is perhaps unsurprising: exposure time resulting from a single game – even a consequential one – is unlikely to produce long-lasting effects.

7 Conclusion

This paper examines how racial animus responds to the presence and performance of minority star athletes in team sports, focusing on Black quarterbacks in the National Football League (NFL). By analyzing reactions to Black quarterbacks in NFL games, we provide new evidence on how highly visible athletes in one of America's most prominent cultural institutions shape public attitudes and behaviors toward minority groups both around game days and over the course of a season.

First, using an event study design, we investigate how racial animus changes in the very short-run – the five days surrounding games. We find evidence of a racial retaliation effect whereby racial animus is directed toward local Black populations when a salient Black quarterback is involved – and thereby "blamable" – for the negative affect shock generated by emotionally engaging losses. Relative to games where both quarterbacks were white, losses involving a Black quarterback are followed by a 16% increase in the hate crime rate. This effect is driven by emotionally engaging games – close scoring games where the loss was an upset outcome. These games experience a 40% increase in the hate crime rate. In contrast, unengaging losses – that are neither close scoring nor upset games – are associated with a much smaller, statistically insignificant increases of 6.4%. These short-run increases in racial animus after engaging losses extend beyond hate crimes. We observe a 36% increase in moderation on reddit and a 0.035 sd increase in IAT scores following such games.

Crucially, short-run emotion-driven retaliation operates alongside a long-run performance-contingent updating process in which exposure to Black quarterbacks shapes racial attitudes based on team performance. In areas with low performing Black quarterback teams that do not reach the playoffs, hate crime rates, moderation on reddit, and IAT scores are unaffected while google searches for racial slurs increase by 0.059 standard deviations. In contrast, we observe significant drops in racial animus during and after seasons where Black quarterback led teams make it to the championship games. In the months following the NFL season, these areas experience hate crime rates that are 32% lower, declines in racial slur searches of -0.082 standard deviations, a 17% reduction in the share of reddit submissions being moderated, and a -0.040 standard deviation decline in implicit racial biases. Finally, we find no evidence that increased exposure to opposition Black quarterbacks generates any long-run persistent changes in racial animus.

Taken together, these findings highlight two distinct mechanisms through which highly visible sporting events shape racial hostility. In the short run, emotionally engaging losses involving Black quarterbacks generate spikes in racial animus consistent with racial retaliation. Over longer horizons, however, repeated exposure to successful Black quarterbacks appears to shift racial attitudes in ways consistent with performance-based updating. These results have several implications for future work on media representation. First, researchers should consider the role of time horizons and context—including emotional responses and perceived performance—when interpreting results and assessing generalizability. Second, the transition from short-run emotional reactions to longer-run attitude updating remains understudied, suggesting a promising direction for future research.

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8 Tables

Table 1: Summary statistics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel a: Game day data									
	Units	Obs. level	Weights	Seasons	Obs.	Games x teams	Season x teams	Mean	Std. Dev
Anti-Black hate crimes	Crimes per 10 mil.	Date x DMA	DMA population	2002 - 2024	306625	9709	729	0.156	1.950
IAT score	Std. dev.	Individual tests		2002 - 2024	708969	9062	702	0.186	0.947
Share removed	Share	Date x Subreddit	Submission count	2010 - 2024	25425	5119	417	0.068	0.103
Appendix outcomes									
Submissions	Count	Date x Subreddit		2010 - 2024	25425	5119	417	54	78
Anti-Black hate speech	ToxiGen score	Date x Subreddit	Submission count	2010 - 2024	22058	5119	417	0.00011	0.00254
IAT count	Count	Date x DMA		2002 - 2024	130311	9062	702	5.4	11.2
Panel b: Season data									
	Units	Obs. level	Weights	Seasons	Obs.		Season x teams	Mean	Std. Dev
Hate crimes	Crimes per 100,000	Date x DMA	DMA population	2002 - 2024	52028		713	0.050	0.132
Google slur searches	Std. index	2 Months x DMA	DMA population	2004 - 2023	15432		613	-0.150	0.811
IAT score	Std. index	Individuals tests		2002 - 2024	3761683		713	0.168	0.949
Share removed	Share	Month x Subreddit	Submission count	2011 - 2024	4751		446	0.076	0.077
Appendix outcomes									
Submissions	Count	Month x Subreddit		2011 - 2024	4751		446	933	964
Anti-Black hate speech	Toxigen score	Month x Subreddit	Submission count	2011 - 2024	4528		446	0.00010	0.00057
IAT count	Count	Month x DMA		2002 - 2024	48518		713	78	172

Table 2: Game day impacts on hate crimes

	(1) All	(2) Close-upsets	(3) Either	(4) Neither
White-white games:				
Post	-0.00480	-0.00732	-0.00141	-0.00878
	(0.0163)	(0.0369)	(0.0202)	(0.0267)
Post × *Win*	-0.00317	0.0273	-0.00891	0.00358
	(0.0114)	(0.0295)	(0.0152)	(0.0171)
Any Black quarterback games:				
Post × *Any Black QB*	0.0300**	0.0754**	0.0420**	0.0120
	(0.0126)	(0.0318)	(0.0167)	(0.0190)
Post × *Any Black QB* × *Win*	-0.0178	-0.107**	-0.0269	-0.00363
	(0.0174)	(0.0457)	(0.0231)	(0.0264)
$\rho_2^b + \rho_4^b$	0.012	-0.032	0.015	0.008
Dependent mean	0.189	0.189	0.189	0.189
Observations	306625	44715	172405	134220
Game × teams	9709	1401	5471	4238

Note: Standard errors are reported in parentheses, with the following significance indicators: * p<0.1, ** p<0.05 and *** p<0.01.

Table 3: Game day impacts on hate speech indicators and IAT scores

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Submission removals				White IAT scores			
	All	Close-upsets	Either	Neither	All	Close-upsets	Either	Neither
White-white games:								
Post	0.0575***	0.0350	0.0550***	0.0592***	-0.0103	0.0106	-0.00917	-0.0131
	(0.00809)	(0.0223)	(0.0113)	(0.00966)	(0.0109)	(0.0248)	(0.0150)	(0.0151)
Post × *Win*	-0.0276***	-0.00541	-0.0281***	-0.0268***	-0.00370	0.0189	0.000448	-0.00890
	(0.00515)	(0.0154)	(0.00744)	(0.00644)	(0.00737)	(0.0191)	(0.0101)	(0.0107)
Any Black quarterback games:								
Post × *Any Black QB*	0.00973	0.0461***	0.0152*	0.00168	0.00347	0.0348*	0.0132	-0.00883
	(0.00606)	(0.0172)	(0.00850)	(0.00805)	(0.00819)	(0.0200)	(0.0110)	(0.0122)
Post × *Any Black QB* × *Win*	-0.00605	-0.0386*	-0.00751	-0.00359	-0.00400	-0.0548*	-0.0132	0.00852
	(0.00758)	(0.0218)	(0.0105)	(0.0104)	(0.0117)	(0.0298)	(0.0157)	(0.0175)
$\rho_2^b + \rho_4^b$	0.004	0.008	0.008	-0.002	-0.001	-0.020	-0.000	-0.000
Dependent mean	0.115	0.128	0.118	0.109	0.186	0.195	0.187	0.185
Observations	25133	3617	14154	10979	701242	101246	391725	309517
Game × teams	5100	733	2876	2224	8853	1281	4973	3880

Note: Standard errors are reported in parentheses, with the following significance indicators: * p<0.1, ** p<0.05 and *** p<0.01.

Table 4: Engaging game day impacts for local and opposition Black quarterbacks

	(1)	(2)	(3)
	Hate crime rate	Sub. removals	IAT scores
Local Black quarterback games:			
Post × *Only local QB is Black*	0.0890**	0.0571***	0.0259
	(0.0394)	(0.0202)	(0.0217)
Post × *Only local QB is Black* × *Win*	-0.104*	-0.0511*	-0.0558
	(0.0542)	(0.0283)	(0.0356)
Opposition Black quarterback games:			
Post × *Only opp. QB is Black*	0.0589	0.0316	0.0460
	(0.0385)	(0.0199)	(0.0292)
Post × *Only opp. QB is Black* × *Win*	-0.107*	-0.0230	-0.0568
	(0.0601)	(0.0257)	(0.0401)
P-value of $\rho_2^l = \rho_2^o$	.51	.23	.52
P-value of $\rho_2^l + \rho_4^l = \rho_2^o + \rho_4^o$	.52	.91	.58
Dependent mean	0.169	0.076	0.195
Observations	44715	3617	101246
Game × teams	1401	733	1281

Note: Standard errors are reported in parentheses, with the following significance indicators: * p<0.1, ** p<0.05 and *** p<0.01.

Table 5: Season effects of local Black quarterbacks by team performance

	(1) Hate crime rate (monthly DMA)	(2) Google slur index (Standardized)	(3) Submission removals (Share)	(4) IAT scores (Standardized)
Not in playoffs				
Main QB is Black × After season	-0.000129	0.0587**	0.000810	0.00199
	(0.00359)	(0.0293)	(0.0113)	(0.00559)
In playoffs only				
Main QB is Black × After season × In playoffs only	-0.00321	-0.0542	-0.00718	-0.000548
	(0.00730)	(0.0464)	(0.0132)	(0.0100)
In championships				
Main QB is Black × After season × In championship	-0.0158*	-0.141***	-0.0157	-0.0421***
	(0.00898)	(0.0538)	(0.0188)	(0.0138)
Compared to white QB championship teams:	-0.016*	-0.082*	-0.015	-0.040***
Dep. mean	0.0500	-0.151	0.0760	0.168
Observations	52028	15414	4574	3761643
Team × seasons	713	613	427	713

Note: Standard errors are reported in parentheses, with the following significance indicators: * $p<0.1$, ** $p<0.05$ and *** $p<0.01$.

Table 6: Season effects of opposition quarterback's race

	(1) Hate crimes (monthly DMA)	(2) Google slur index	(3) Submission removals (Share)	(4) IAT scores (Standardized)
Panel a: Effects of opposition quarterback games in the regular season				
Games against Opp. Black QBs × After season	0.00137	-0.00160	-0.000650	0.000511
	(0.00114)	(0.00621)	(0.00154)	(0.00137)
Dependent mean	0.0516	-0.132	0.0706	0.180
Observations	39744	11430	3454	2800801
Panel b: Effects of opposition quarterback games in the regular season by game outcome				
Losses against Opp. Black QBs × After season	0.000181	-0.0112	-0.000433	-0.000900
	(0.00179)	(0.00848)	(0.00209)	(0.00191)
Wins against Opp. Black QBs × After season	0.00231*	0.00829	-0.00116	0.00214
	(0.00128)	(0.00858)	(0.00175)	(0.00177)
Dependent mean	0.0516	-0.132	0.0706	0.180
Observations	39744	11430	3454	2800801
Panel c: Effects of being knocked out by an opposition Black quarterback team				
Knockout QB is Black × After season	-0.0130*	0.00960	-0.0110	-0.00507
	(0.00770)	(0.0522)	(0.0136)	(0.00930)
Dependent mean	0.0488	-0.0845	0.0750	0.177
Observations	13648	3888	1099	943242

Note: Standard errors are reported in parentheses, with the following significance indicators: * p<0.1, ** p<0.05 and *** p<0.01.

9 Figures

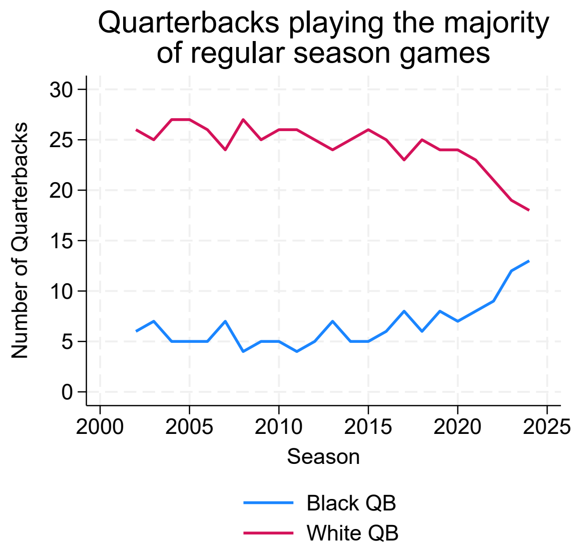

Figure 1: Black quarterbacks in the NFL

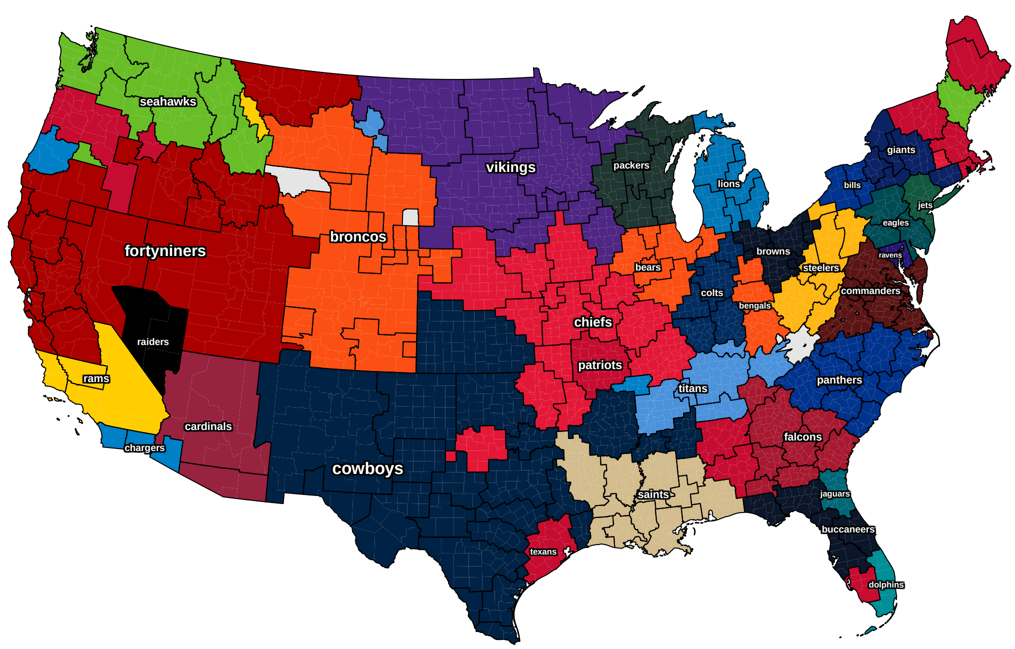

Figure 2: NFL team catchment areas

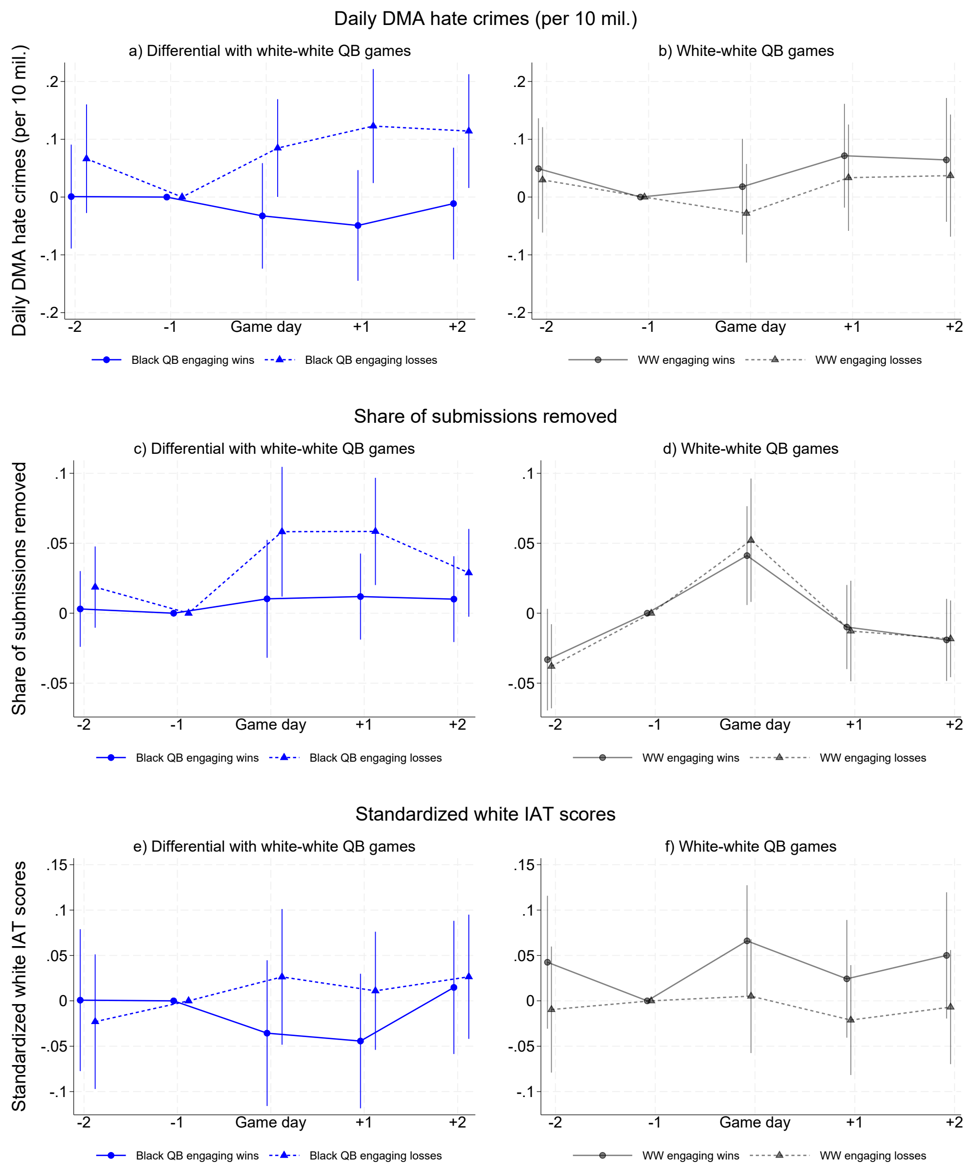

Figure 3: Game day effects of Black QBs

Notes: Figures on the left plot the differential effect of Black quarterbacks for engaging games as estimated by equation 6. The ρ_2^b estimates are plotted for engaging losses and the $(\rho_2^b + \rho_4^b)$ estimates for engaging wins. Figures on the right plot the ρ_1^w estimates and the $(\rho_1^w + \rho_3^w)$ estimates showing the effects of engaging losses and wins around white-white quarterback games.

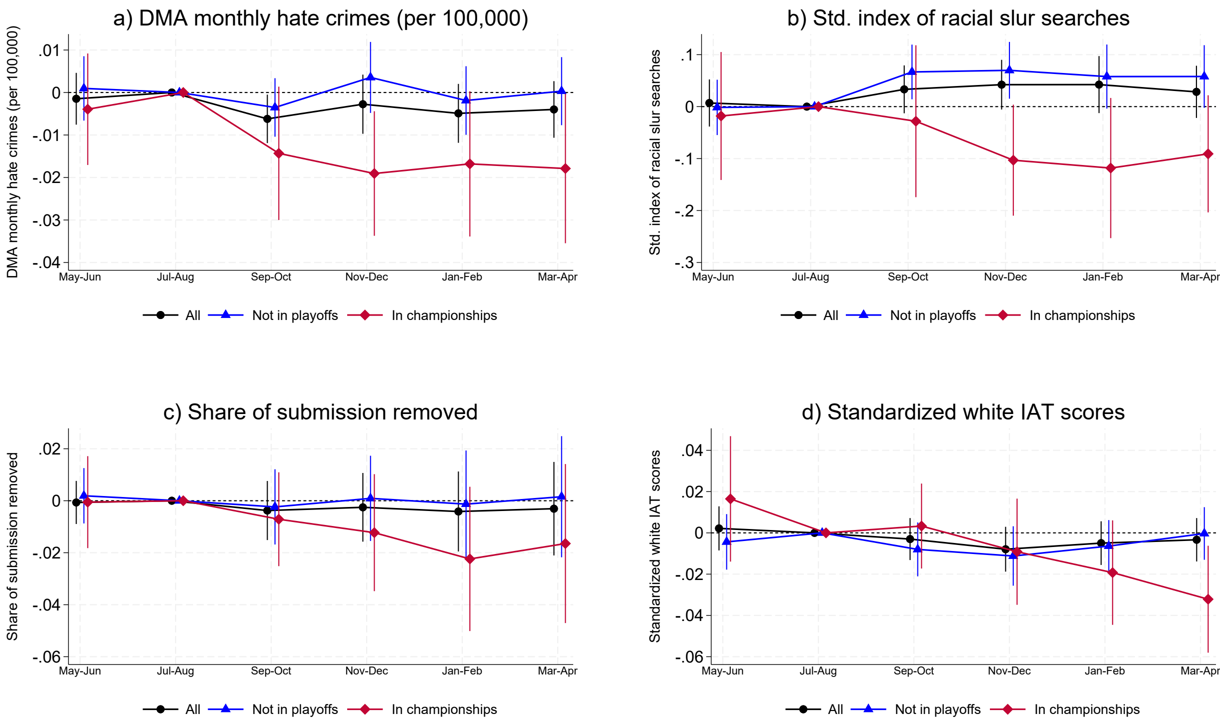

Figure 4: Long-run effects of local Black QBs

Notes: Figures plot the μ_T^r and μ_T^c from equation 7 in blue and red respectively. Aggregate estimates for all performance levels are plotted in black. These estimates control for $location \times season$, $month \times location$, $month \times record$, and $month \times season$ fixed effects.

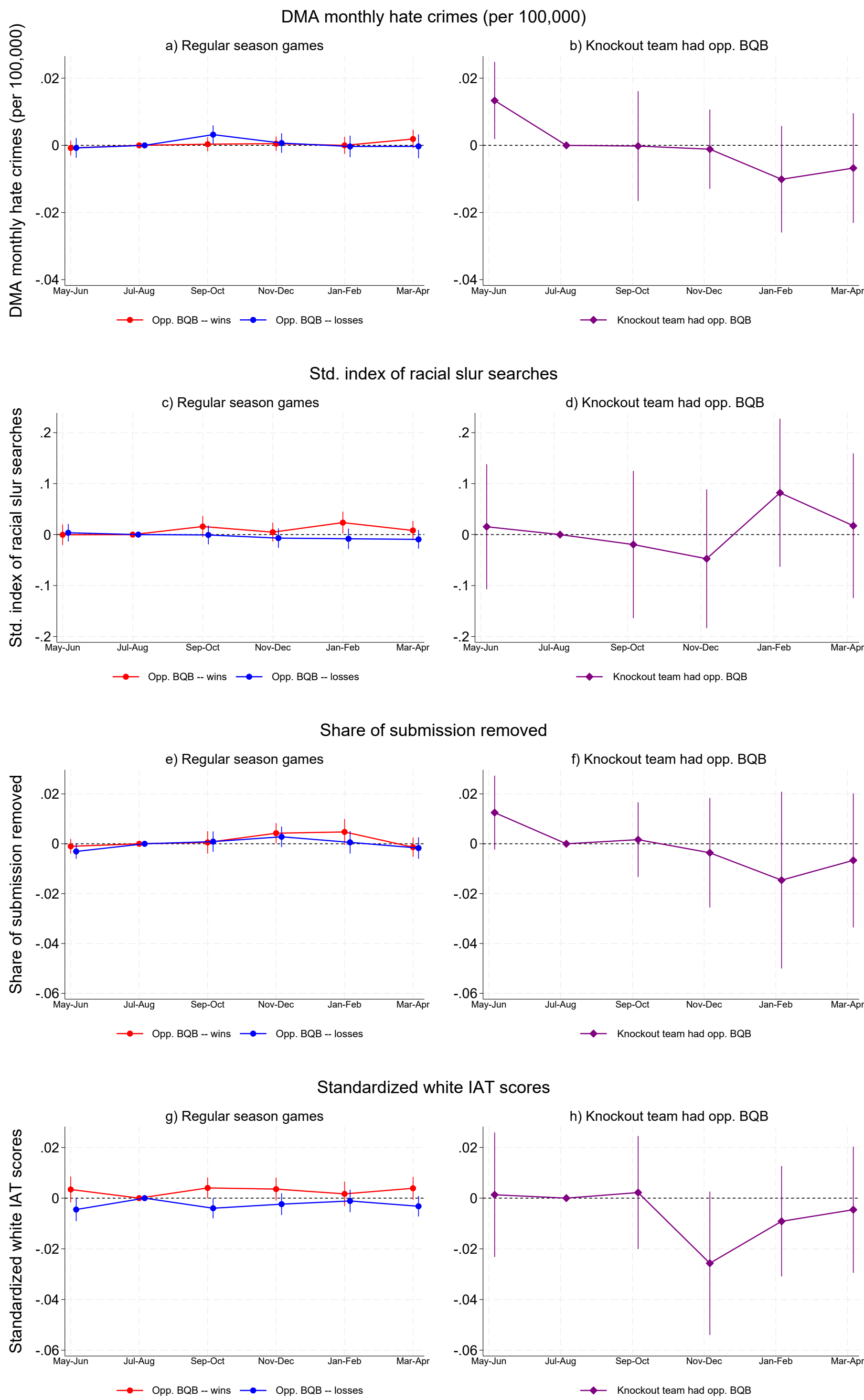

Figure 5: Long-run effects of opposition Black QBs

Notes: For all figures, the sample is limited to team-seasons where the main quarterback was white. Figures on the left plot the differential effect of an additional regular season game played against opposition Black quarterbacks. Figures on the right plot the differential effect of being knocked out of the playoffs by a team with an Black quarterback.

Online Appendix

A1 Appendix Tables

Table A1: Robustness to alternative outcome measures of daily DMA hate crimes

	Main (incidents per 10 mil.)	Extensive indicator (1 if has incidents)	Zero adjusted log log(incidents+1)	Linear raw (incident count)	Poisson raw (incident count)	Unweighted main
Panel a: All games						
Post × Any Black QB	0.0300**	0.00337**	0.00286**	0.00473**	0.149**	0.0654***
	(0.0126)	(0.00166)	(0.00124)	(0.00195)	(0.0669)	(0.0198)
Post × Any Black QB × Win	-0.0178	-0.00143	-0.00156	-0.00296	-0.0984	-0.0227
	(0.0174)	(0.00224)	(0.00166)	(0.00260)	(0.0937)	(0.0287)
Dependent mean	0.189	0.025	0.019	0.028	0.288	0.156
Observations	306625	306625	306625	306625	30095	306625
Panel b: Close upset games						
Post × Any Black QB	0.0754**	0.00866**	0.00673**	0.0106**	0.439**	0.151***
	(0.0318)	(0.00396)	(0.00293)	(0.00447)	(0.181)	(0.0565)
Post × Any Black QB × Win	-0.107**	-0.0120**	-0.00958**	-0.0154**	-0.590**	-0.203***
	(0.0457)	(0.00600)	(0.00442)	(0.00674)	(0.242)	(0.0740)
Dependent mean	0.189	0.025	0.018	0.028	0.279	0.169
Observations	44715	44715	44715	44715	4440	44715
Panel c: Neither games						
Post × Any Black QB	0.0120	0.00167	0.00137	0.00212	0.0333	0.0323
	(0.0190)	(0.00255)	(0.00193)	(0.00307)	(0.0993)	(0.0313)
Post × Any Black QB × Win	-0.00363	-0.000147	-0.000362	-0.000920	-0.00327	0.0183
	(0.0264)	(0.00338)	(0.00253)	(0.00400)	(0.143)	(0.0412)
Dependent mean	0.189	0.025	0.019	0.028	0.290	0.151
Observations	134220	134220	134220	134220	13140	134220

Note: Standard errors are reported in parentheses, with the following significance indicators: * p<0.1, ** p<0.05 and *** p<0.01.

Table A2: Robustness to fixed effects

	(1)	(2)	(3)	(4)
Panel a: All games				
Post × *Any Black QB*	0.029999**	0.030279**	0.030284**	0.030283**
	(0.012551)	(0.012550)	(0.012550)	(0.012554)
Post × *Any Black QB* × *Win*	-0.017805	-0.017765	-0.017774	-0.017773
	(0.017386)	(0.017393)	(0.017393)	(0.017399)
Dependent mean	0.189	0.189	0.189	0.189
Observations	306625	306625	306625	306625
Panel b: Close upset games				
Post × *Any Black QB*	0.075353**	0.075698**	0.075704**	0.075702**
	(0.031849)	(0.031728)	(0.031728)	(0.031802)
Post × *Any Black QB* × *Win*	-0.106997**	-0.106055**	-0.106061**	-0.106061**
	(0.045656)	(0.045636)	(0.045636)	(0.045742)
Dependent mean	0.189	0.189	0.189	0.189
Observations	44715	44715	44715	44715
Panel c: Neither games				
Post × *Any Black QB*	0.012034	0.012587	0.012592	0.012591
	(0.018957)	(0.018971)	(0.018971)	(0.018985)
Post × *Any Black QB* × *Win*	-0.003633	-0.003653	-0.003659	-0.003658
	(0.026363)	(0.026365)	(0.026365)	(0.026385)
Dependent mean	0.189	0.189	0.189	0.189
Observations	134220	134220	134220	134220
FE: DMA × Game-team	Yes	Yes	No	No
FE: Day of the week	Yes	No	No	No
FE: DMA	.	.	No	Yes
FE: Game-team	.	.	Yes	Yes

Note: Standard errors are reported in parentheses, with the following significance indicators: * p<0.1, ** p<0.05 and *** p<0.01.

Table A3: **Game day impacts on other hate crimes**

	(1) Anti-Black	(2) Anti-white	(3) Anti-Hispanic	(4) Anti-other race
White-white games:				
Post	-0.00732	-0.0252	0.0122	0.00936
	(0.0369)	(0.0221)	(0.0168)	(0.0215)
Post × *Win*	0.0273	0.00216	0.0241*	-0.00760
	(0.0295)	(0.0159)	(0.0130)	(0.0186)
Any Black quarterback games:				
Post × *Any Black QB*	0.0754**	0.00846	0.00382	-0.00150
	(0.0318)	(0.0167)	(0.0133)	(0.0187)
Post × *Any Black QB* × *Win*	-0.107**	0.00316	-0.0443**	0.0225
	(0.0457)	(0.0243)	(0.0205)	(0.0263)
$\rho_2^b + \rho_4^b$	-0.032	0.012	-0.040***	0.021
Dependent mean	0.189	0.059	0.040	0.060
Observations	44715	44715	44715	44715
Game × teams	1401	1401	1401	1401

Note: Standard errors are reported in parentheses, with the following significance indicators: * p<0.1, ** p<0.05 and *** p<0.01.

Table A4: Game day impacts on submission numbers, anti-Black speech and IAT test taking – Close-upset games

	(1) Submissions	(2) Anti-Black speech	(3) IAT test takers
White-white games:			
Post	85.59***	0.00000410	0.173
	(9.552)	(0.0000373)	(0.159)
Post × *Win*	13.42**	-0.000221	-0.101
	(5.838)	(0.000198)	(0.189)
Any Black quarterback games:			
Post × *Any Black QB*	-2.778	0.0000870	-0.166
	(4.860)	(0.000120)	(0.146)
Post × *Any Black QB* × *Win*	10.74	0.000188	0.125
	(10.30)	(0.000234)	(0.217)
Win test	7.96	0.000	-0.041
Dependent mean	57.626	0.000	2.374
Observations	3653	3103	42365
Game × teams	733	622	1266

Note: Standard errors are reported in parentheses, with the following significance indicators: * p<0.1, ** p<0.05 and *** p<0.01.

Table A5: Changes in hate crimes do not predict quarterback race

	(1)	(2)	(3)	(4)
	Main QB is Black			
Std. change in hate crimes from *s*-2 to *s*-1	-0.0162	0.00146	0.000652	-0.00114
	(0.0182)	(0.0154)	(0.0153)	(0.0140)
s-1 season QB was Black		0.472***	0.382***	
		(0.0430)	(0.0485)	
s-2 season QB was Black		0.120***	0.103**	
		(0.0433)	(0.0429)	
s-1 season made championships			-0.0614	
			(0.0479)	
s-1 season made playoffs only			-0.0408	
			(0.0355)	
s-1 season made championships with Black QB			0.433***	
			(0.114)	
s-1 season made playoffs only with Black QB			0.211***	
			(0.0787)	
Observations	586	586	586	437
FE: Team	Yes	Yes	Yes	Yes
FE: Season	Yes	Yes	Yes	Yes
Subsample: Had a white QB in *s*-1 and *s*-2				Yes

Note: Standard errors are reported in parentheses, with the following significance indicators: * p<0.1, ** p<0.05 and *** p<0.01.

Table A6: Season effects of local Black quarterbacks – robustness

	(1) Main (DMA/mo/100k)	(2) Extensive indicator (1 if has incidents)	(3) Zero adjusted log log(incidents+1)	(4) Linear raw (incident count)	(5) Poisson raw (incident count)	(6) Unweighted main
Not in playoffs						
Main QB is Black × After season	-0.000129	-0.0177	-0.0212	-0.0208	0.0188	-0.0121**
	(0.00359)	(0.0170)	(0.0170)	(0.0613)	(0.0567)	(0.00526)
In playoffs only						
Main QB is Black × After season × In playoffs only	-0.00321	0.0124	0.0180	-0.0475	-0.0956	0.00509
	(0.00730)	(0.0278)	(0.0322)	(0.118)	(0.103)	(0.00956)
In championships						
Main QB is Black × After season × In championship	-0.0158*	-0.0403	-0.0437	-0.130	-0.334**	-0.0106
	(0.00898)	(0.0372)	(0.0421)	(0.144)	(0.135)	(0.0121)
Compared to white QB championship teams:	-0.016*	-0.058*	-0.065*	-0.151	-0.315***	-0.023**
Dependent mean	0.059	0.318	0.355	0.891	1.272	0.050
Observations	52028	52028	52028	52028	36444	52028

Note: Standard errors are reported in parentheses, with the following significance indicators: * p<0.1, ** p<0.05 and *** p<0.01.

Table A7: Season estimates for local Black quarterbacks – Robustness to fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Hate crime rate						
Not in playoffs							
After season		-0.0120***	-0.0103***				
		(0.00250)	(0.00212)				
Main QB is Black × After season	-0.000129	-0.00160	-0.00314	-0.000943	-0.00321	0.00139	-0.00333
	(0.00359)	(0.00501)	(0.00366)	(0.00346)	(0.00353)	(0.00373)	(0.00480)
In playoffs only							
After season × In playoffs only		0.00415	-0.000593				
		(0.00421)	(0.00354)				
Main QB is Black × After season × In playoffs only	-0.00321	-0.00575	0.000769	0.000283	0.00450	-0.00506	-0.00393
	(0.00730)	(0.00807)	(0.00628)	(0.00622)	(0.00633)	(0.00714)	(0.00868)
In championships							
After season × In championship		0.00783	0.000471				
		(0.00600)	(0.00413)				
Main QB is Black × After season × In championship	-0.0158*	-0.0204**	-0.0105	-0.0100*	-0.00548	-0.0178**	-0.0212*
	(0.00898)	(0.0100)	(0.00689)	(0.00589)	(0.00715)	(0.00758)	(0.0111)
Compared to white QB championship teams:	-0.016*	-0.022**	-0.014**	-0.011**	-0.009	-0.016**	-0.024**
Observations	52028	52028	52028	52028	52028	52028	52028
FE: DMA × season	Yes	Yes	No	Yes	Yes	Yes	Yes
FE: Month × season	Yes	No	No	Yes	Yes	Yes	No
FE: DMA × month	Yes	No	No	No	Yes	No	Yes
FE: Record × month	Yes	No	No	No	No	Yes	Yes
FE: DMA	.	.	Yes	.	.	.	.
FE: Season	.	.	Yes	.	.	.	.

Note: Standard errors are reported in parentheses, with the following significance indicators: * p<0.1, ** p<0.05 and *** p<0.01.

Table A8: Season effects of local Black quarterbacks by team performance

	(1) Anti-Black	(2) Anti-White	(3) Anti-Hispanic	(4) Anti-Other race
Not in playoffs				
Main QB is Black × After season	-0.000129	-0.000763	-0.00113	-0.00326
	(0.00359)	(0.00199)	(0.00151)	(0.00234)
In playoffs only				
Main QB is Black × After season × In playoffs only	-0.00321	-0.00226	0.00445	0.00261
	(0.00730)	(0.00390)	(0.00278)	(0.00382)
In championships				
Main QB is Black × After season × In championship	-0.0158*	-0.00153	0.00391	0.00458
	(0.00898)	(0.00443)	(0.00323)	(0.00495)
Dep. mean	0.0594	0.0189	0.0125	0.0180
Observations	52028	52028	52028	52028

Note: Standard errors are reported in parentheses, with the following significance indicators: * p<0.1, ** p<0.05 and *** p<0.01.

Table A9: Season effects of local Black quarterbacks by team performance – appendix outcomes

	(1) Submissions	(2) Anti-Black hate speech	(3) IAT tests
Not in playoffs			
Main QB is Black × After season	11.57	0.000109*	0.212
	(78.20)	(0.0000657)	(0.180)
In playoffs only			
Main QB is Black × After season × In playoffs only	-26.05	-0.000107	-0.532
	(92.22)	(0.0000983)	(0.376)
In championships			
Main QB is Black × After season × In championship	61.60	-0.0000719	0.351
	(229.7)	(0.000195)	(0.405)
Compared to white QB championship teams:	73.2	0.000	0.563
Dep. mean	940.6	0	5.392
Observations	4578	4364	697575
Team × seasons	428	397	713

Note: Standard errors are reported in parentheses, with the following significance indicators: * p<0.1, ** p<0.05 and *** p<0.01.

Table A10: Season effects of opposition Black quarterbacks – alternative measures of hate crimes

	(1) Main (DMA/mo/100k)	(2) Extensive indicator (1 if has incidents)	(3) Zero adjusted log log(incidents+1)	(4) Linear raw (incident count)	(5) Poisson raw (incident count)	(6) Unweighted main
Panel a: Effects of opposition quarterback games in the regular season						
Games against Opp. Black QBs × After season	0.00137	-0.00211	0.00303	-0.123	0.0356**	0.00127
	(0.00114)	(0.00600)	(0.0136)	(0.178)	(0.0150)	(0.00153)
Dependent mean	0.052	0.325	0.365	0.929	1.327	0.052
Observations	39744	39744	39744	39744	27803	39744
Panel b: Effects of being knocked out by an opposition Black quarterback team						
Knockout QB is Black × After season	-0.0130*	-0.0190	-0.0387	0.460	-0.163	-0.0270**
	(0.00770)	(0.0443)	(0.0763)	(0.667)	(0.108)	(0.0106)
Dependent mean	0.049	0.297	0.321	0.779	1.289	0.049
Observations	13648	13648	13648	13648	8224	13648

Note: Standard errors are reported in parentheses, with the following significance indicators: * p<0.1, ** p<0.05 and *** p<0.01.

A2 Appendix Figures

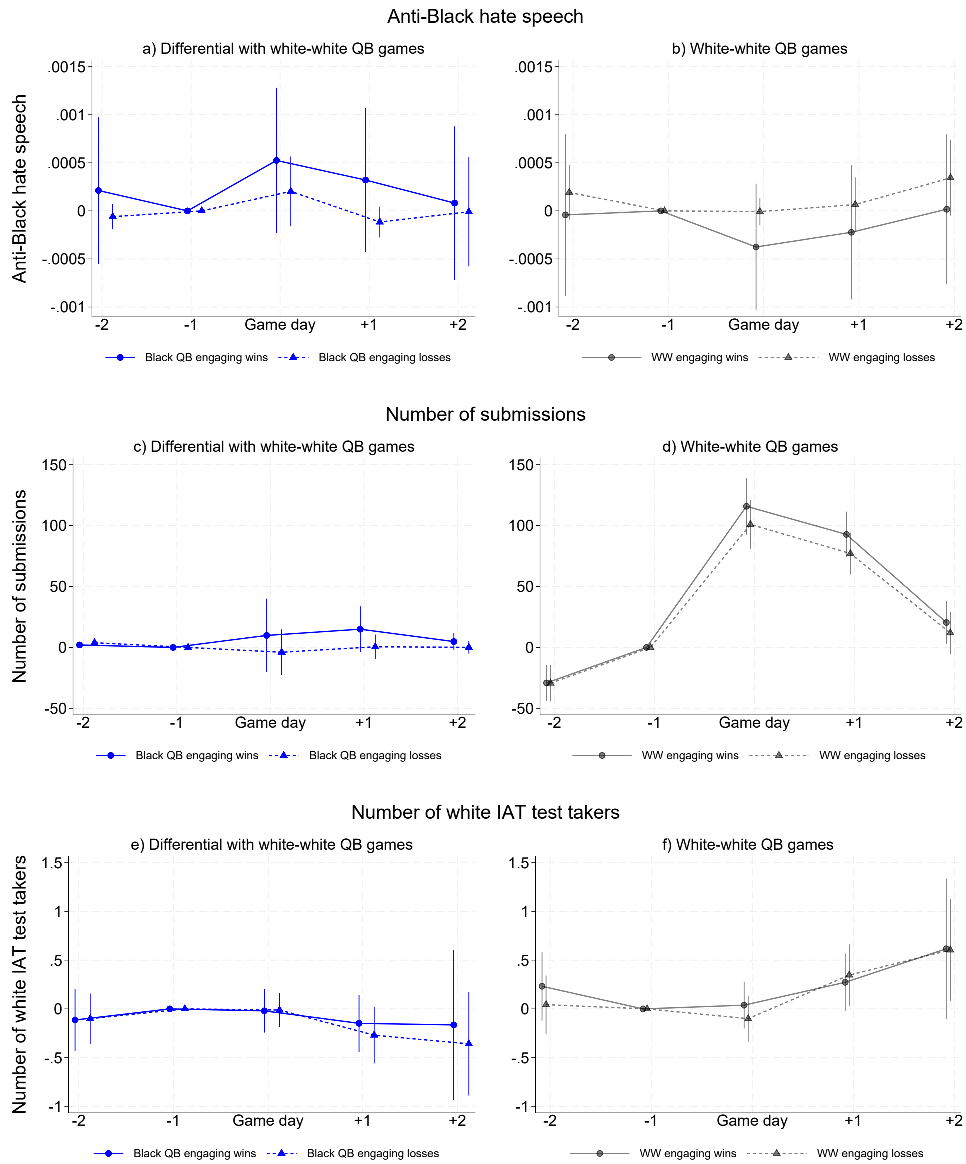

Figure A1: Game day effects of local Black quarterbacks

Figures on the left plot the differential effect of local Black quarterbacks for engaging games as estimated by equation 6. The ρ_2^b estimates are plotted for engaging losses and the $(\rho_2^b + \rho_4^b)$ estimates for engaging wins. Figures on the right plot the ρ_1^w estimates and the $(\rho_1^w + \rho_3^w)$ estimates showing the effects of engaging losses and wins around white-white quarterback games.

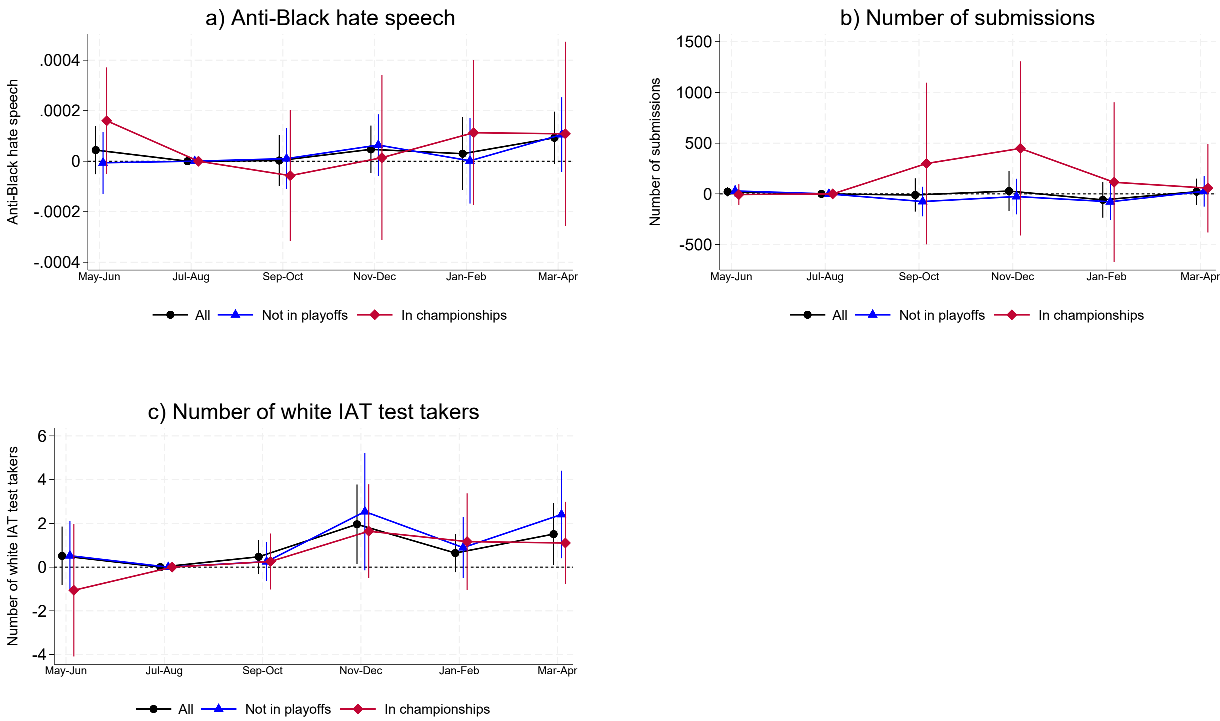

Figure A2: Long-run effects of local Black QBs

Notes: Figures plot the μ_T^r and μ_T^c from equation 7 in blue and red respectively. Aggregate estimates for all performance levels are plotted in black. These estimates control for $location \times season$, $month \times location$, $month \times record$, and $month \times season$ fixed effects.

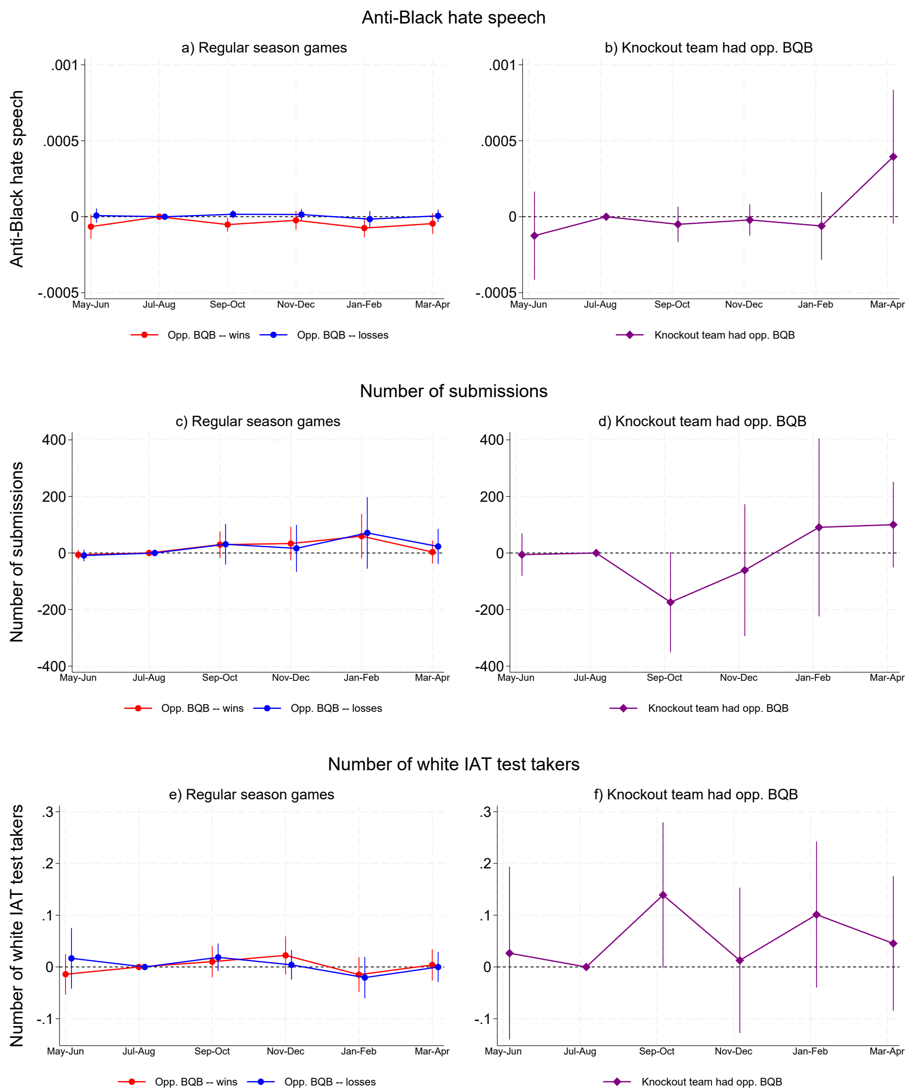

Figure A3: Long-run effects of opposition Black QBs

Notes: For all figures, the sample is limited to team-seasons where the main quarterback was white. Figures on the left plot the differential effect of an additional regular season game played against opposition Black quarterbacks. Figures on the right plot the differential effect of being knocked out of the playoffs by a team with an Black quarterback.