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# The Giannis Effect: How Celebrities Impact Prejudice in Their Communities

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# The Giannis Effect
## How Celebrities Impact Prejudice in Their Communities

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**Abstract**

This paper examines the effect Giannis Antetokounmpo, a Greek-Nigerian NBA player for the Milwaukee Bucks, has had on bias towards immigrants and Black people in Milwaukee and in Wisconsin as a whole. This work is based on the breakthrough 2021 study from Alrababa'h et al., which found that Liverpool FC's signing of star Muslim footballer Mohamed Salah dramatically reduced public instances of islamophobia in Liverpool. Using Synthetic Control (SC) and Synthetic Difference in Difference (SDID) frameworks, I implement two methods of analysis to examine Giannis's influence: an examination of Anti-Black and Anti-Immigrant hate crimes in the US, and analysis of Anti-Immigrant google searches in Wisconsin and surrounding states. The results indicate substantial reductions in hate crimes and Anti-Immigrant Google searches in Wisconsin since Giannis was drafted in 2013, though data quality issues make it difficult to draw firm conclusions. This study demonstrates the power of positive Parasocial Contact in changing attitudes and reducing biases.

Department of Economics, Macalester College

Advisor: Mario Solis-Garcia

1 May 2023

# 1 Introduction

However prevalent you think racial and ethnic bias are in your community, it's probably worse. Domestic extremism is on the rise in the United States: 2020 saw the most reported hate crimes in two decades, and 20% more than that were reported in 2021 (Levin, 2022). Racially charged language is surging in popular discourse as well. An Ipsos poll found that, as of April 28th, 2020, 60% of Asian-Americans had reported witnessing someone blaming people of Asian descent for the Coronavirus pandemic, a message frequently pushed by then-president Donald Trump (Jackson et al., 2020).

The U.S. is said to be fighting the dual pandemics of COVID-19 and systemic racism (Jones, 2021). Coronavirus has further exposed how the negative consequences of threats to our society, whether from climate change, a pandemic or other sources of societal stress, fall disproportionately on marginalized communities. These burdens will persist until our society has been thoroughly cleansed of the mechanisms that benefit whites at the expense of people of color.

Reductions in racial and ethnic prejudice improve the wellbeing of individuals and communities. A less biased community becomes safer, more trusting, and more socially cohesive. Recent work from Raj Chetty (2020) has found that Black boys that grow up in integrated, low-bias neighborhoods have greater economic success later in life as compared to their counterparts from segregated or prejudiced communities. However, only 4% of Black children currently grow up in desegregated, low-bias neighborhoods (Chetty, 2020); creating more of these environments should be considered essential part of pursuing a more equitable future.

All this begs the question: what factors reduce racial or ethnic prejudice in our own communities? In a perfect world, people of all races and ethnicities would interact with one another on a consistent basis, which according to the *Contact Hypothesis* (Allport, 1954), would create close-knit communities with little bias. Having conversations with people holding different identities than yourself often makes you realize that you aren't so different after all. Unfortunately, most people live, work, and shop around other people that look like them (Enos, 2017). In these cases, exposure to outgroups, or people with different identities than oneself, must come through alternative means. One such apparatus is *parasocial contact*, wherein exposure to others is mediated through television, radio, a live event, or other channels (Schippa, Gregg, and Hewes, 2005), essentially creating a one-way connection between the audience and the performer(s).

Prior research has explored the impact of celebrities on community-level prejudice outcomes. Alrababa'h et al. (2021) found using primarily Twitter and hate crimes data that Mohamed Salah, a renowned Muslim footballer, reduced Anti-Muslim prejudice amongst fans of Liverpool F.C. upon joining the team in 2017. The authors' findings present evidence of the parasocial contact hypothesis in sports.

In this study, I follow the lead of Alrababa'h et al. (2021) and examine the impact of Giannis Antetokounmpo, an star NBA player for the Milwaukee Bucks, on prejudice among his fans and within his community. This study will make several contributions to the existing literature. This study serves as another test of parasocial contact theory, using both a new subject (Giannis) and a new setting (Wisconsin). While prior research has studied anti-Black or anti-Muslim sentiment (Alrababa'h et al., 2021; Stephens-Davidowitz, 2014), I will measure Anti-Black *and* anti-immigrant bias in Wisconsin. I hypothesize that Giannis has reduced both anti-Black and anti-immigrant bias amongst Wisconsinites. Additionally, I posit that the recent success of the Bucks could be reducing Geographic Outgroup Bias—where lack of interaction between racial groups increases bias—which has historically been a leading cause of discrimination in Wisconsin (Enos, 2017).

In Section 2, I introduce Giannis Antetokounmpo and his rise to stardom since entering the NBA in 2013. Section 3 provides further explanations of the Theories of Contact and Parasocial Contact, and their connections to Giannis as a candidate for changing attitudes. In Section 4 I employ two modes of analysis to test my hypothesis: An analysis of hate crimes in the US, and an analysis of Google Trends data. The theory indicates that Giannis's influence will lead to lower levels of anti-Black and anti-immigrant hate crimes, and fewer online searches for anti-Black and anti-immigrant terms. Sections 5 and 6 provide a discussion of my findings and the limitations of my work, respectively. Finally, Section 7 summarizes the key implications of my work, and outlines propositions for future research.

## 2 Background: Who is Giannis Antetokounmpo?

On July 20th, 2021, downtown Milwaukee was buzzing like never before. People of all ages and races, hailing from all over Wisconsin, had gathered in the Deer District surrounding Fiserv Forum for the Milwaukee Bucks' Game 6 NBA Finals matchup against the Phoenix Suns. It was later estimated that by, 8pm tipoff, more than 65,000 fans had huddled together to watch the game on a single inflatable projector screen outside the stadium; many of them were standing in alleyways or behind structures that made actually watching the game impossible, but few particularly cared. Three hours later, the Bucks won the NBA Championship, their first in 50 years.

Just six years prior, the mere idea of taking over a city block to construct the Deer District was met with heavy skepticism. At a 2015 Milwaukee City Council meeting in which Bucks ownership pitched their plans for a new stadium to replace the dilapidated Bradley Center, Alderman Mark Borkowski made his dissent clear (Kraemer, 2021):

> *"I'm sorry to be the wet blanket, but somebody's gotta say it. You hear them talk about all this investment, all of this investment but you know what, it's gonna come at a price. And my fear is it's gonna be a negative effect to the city."*

At the time, Borkowski's worries were not unfounded. The previous year, during the 2013-2014 season, the Bucks finished with a 15-67 record, good for last in the league and their fewest wins in franchise history. Morale was low around the organization, but through some clever scouting (and a good deal of luck) the team's fortunes were about to change.

One of the few bright spots from the dreadful 2013-2014 season was a spindly Greek rookie, whose name was deemed impossible to pronounce by fans, players and announcers alike. Giannis Antetokounmpo made his NBA debut at 18 years old, averaging 7 points and 4 rebounds in his first season. Despite being named one of the 10 best rookies in the league, this was not enough to win over a large number of skeptical viewers. The organization believed in Giannis's ability to develop and become a solid NBA player, but many Bucks fans felt that the team had wasted a first round pick on an unproven, unknown international player.

While Giannis still had a lot of work to do on the court to convince the NBA community that he was drafted for a reason, he was well on his way to becoming a fan favorite through his work ethic and humility. In March of 2014, Sports Illustrated published a story about how Giannis was mailing the most of his contract money back to his family in Greece. Prior to a game in December 2013, he withdrew some money from an ATM and mailed it off, only to realize he didn't have enough cash for a taxi to the game. He opted to run the two miles to the arena instead, eventually hitching a ride with a young couple. As I was developing my own Bucks fandom around this time, stories like these piqued my interest in Giannis and his journey to the league.

Giannis Antetokounmpo grew up as an undocumented Nigerian immigrant in Athens, Greece. His parents left Nigeria before he was born, forced to leave his oldest brother, Francis, behind with his grandparents. Though Giannis and his other brothers—Thanasis, Kostas, and Alex—were all born in Greece, Greek law dictated that they did not automatically receive Greek citizenship; Giannis did not have any documentation until two months before he was drafted. As is documented in the 2022 film *Rise* about Giannis's early life, he grew up hawking souvenirs to tourists and sharing a single bed with his brothers. In an effort to make additional money for their family, Thanasis and Giannis began playing basketball in their early teens.

Now 27, Giannis boasts one of the most impressive resumes in the history of professional basketball. Entering his 10th season in the NBA, he has collected two MVPs, a Defensive Player of the Year Award, and a Finals MVP. He is widely considered to be the best player in the world, and his meteoric rise and continued improvement indicate that the best is yet to come from the superstar.

His on-court accolades are only part of the story, though. Giannis has never been never been afraid to speak his mind on the inequalities present in the US, or on his own experiences as a Black immigrant living in America. He said the following in a post-game press conference in 2021:

> *"My kid is going to grow up here in America and my kid is Black. I cannot imagine my kid going through what I see on TV. And if while I'm living I can do something about it to change it for the better [to the extent] I'm capable of doing, I'm going to do it. I'm going to speak up about it."*

Antetokounmpo was heavily involved in the Black Lives Matter movement in the summer of 2020, leading marches in Milwaukee and spearheading a walkout of an August playoff game following the shooting of Jacob Blake in Kenosha. Wisconsin as a whole is extremely polarized politically, but Giannis has maintained a seemingly ever-growing fanbase during his time in Milwaukee.

## 3 Theoretical Framework

While Giannis has had an impressive impact on the game of basketball, it is less clear whether his successes have translated into broader societal outcomes. This study, will focus on how he has impacted attitudes and behaviors amongst his fans. Alrababa'h et al. (2021) found that Mohamed

Salah, a Muslim footballer for Liverpool FC, dramatically reduced anti-Muslim sentiment among Liverpool fans through his incredible skill and public displays of faith. The Premier League and Britain as a whole have historically had a reputation for Islamophobia, making this result a pleasant and unexpected surprise. Given that Giannis 1) is an incredibly skilled basketball player, 2) is a Black man and an American immigrant, neither of which he is afraid to talk about, and 3) entered a similarly biased situation to Salah (as I will demonstrate in the following paragraphs), I hypothesize that Giannis has decreased prejudice amongst Wisconsinites towards people sharing his identities.

### 3.1 Parasocial Contact Theory

How, exactly, can a single person have such a profound impact on the sentiments held by others? Alrababa'h et al. (2021) point to parasocial contact as the answer. The Parasocial Contact Hypothesis posits that mediated parasocial interaction (i.e., through television or a concert) can simulate interpersonal interaction for the viewer, generating the same benefits that a mutual interaction would (Schippa, Gregg, and Hewes, 2005). This is built off of Gordon Allport's (1954) Contact Hypothesis, which argues that positive interpersonal interaction with an outgroup can reduce prejudice towards that outgroup; essentially, projecting one's sentiments about a single person onto all people that hold their identities. Interacting directly with people of other races and cultures generates empathy and is an important piece of the human experience, but unfortunately our social geographies or internal biases can prevent those interactions from occurring (Enos, 2017). This is why parasocial contact can be such a powerful tool: it can connect a large number of people to another person or group of people at the same time, even if they are not physically in the same space.

### 3.2 Geographic Outgroup Bias

Milwaukee is one of the more diverse cities in the US; as of the 2020 census, about 35% of residents were white, 19% were Latino, and nearly 40% were Black. This alone makes it seem that Milwaukee would be a perfect venue for inter-group contact; however, it is also one of the most segregated cities in the US. Using 2020 census data, Brown University's Diversity and Disparities project found the Milwaukee metro area to be the second most segregated city between Black and white populations in the US (Logan, 2020). This polarization can be seen in Figure 1, which details the demographic breakdown of the Milwaukee metro (Luthern & Mollica, 2019).

**Demographic Map of Milwaukee**

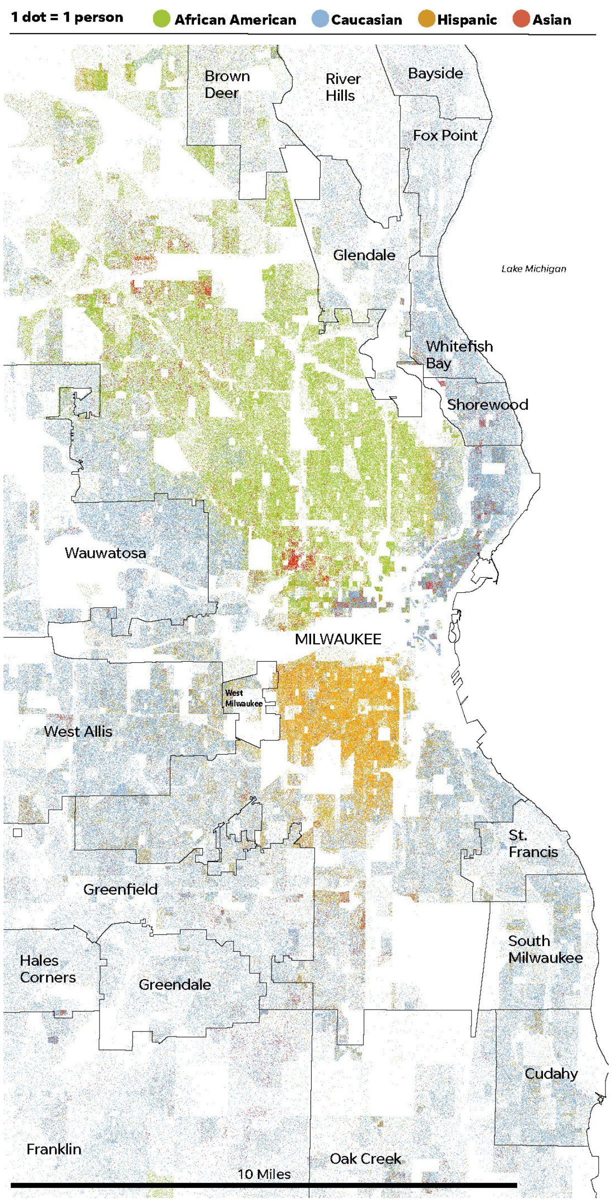



Figure 1: This map from University of Virginia's Weldon Cooper Center for Public Service shows a stark divide between Milwaukee's Black, white, and Hispanic populations.

Because residents of different races typically go to different schools, or attend different places of worship, Milwaukee's racial diversity is largely for naught in terms of creating inter-group interactions. Not only that, but recent scholarship has found that living in close proximity to a large outgroup (like a white neighborhood adjacent to a Black neighborhood) actually creates *more* prejudice than living solely near people with similar racial identities (Enos, 2017). This phenomenon, known as Geographic Outgroup Bias, can create shocking outcomes in a diverse but segregated city: for instance, the average Milwaukee resident is twice as likely to search Google for anti-Black terms like the n-word as residents of Helena, Montana, a city with almost no Black residents but one that is very racially desegregated (Enos, 2017). It should be noted that a number of other Wisconsin metro areas are near the top of the Diversity and Disparities Black-white segregation list, including Eau Claire, La Crosse, Wausau, and Appleton (Logan, 2020). This indicates that segregation between Black and white populations is a pervasive issue throughout Wisconsin.

While the state's residential segregation problem is difficult to remedy quickly, increasing inter-group interaction seems to be a more reasonable task. If Black and white residents of Wisconsin interact more frequently in positive ways, the effects of Geographic Outgroup Bias can be minimized. The Bucks may be exactly what the city of Milwaukee needs to create more of these interactions. The team's sustained success over the last half-decade, along with its 2021 Championship, has led to fan turnout at the Deer District "beyond the wildest dreams" of the developers (Wagner, 2021). Given that the NBA is the only major sports league in the US with a majority nonwhite audience (Silverman, 2020), Bucks games are likely to draw a diverse crowd together around a common cause, creating an ideal setting for positive inter-group interaction.

It is important to note that the success of the Bucks is impossible to disentangle from the success of Giannis himself: the team has improved as he has, and the fan support has followed. It would thus be extremely challenging to separately analyze the effects of the parasocial contact brought on by Giannis and the inter-group contact created by the the Bucks' play. It should be assumed that any reference I make to the "effect of Giannis" includes both the parasocial contact he has with his fans *and* the inter-group interactions that occur amongst Bucks fans.

### 3.3 Context: Mohamed Salah's Impact on Liverpool

Mo Salah signed with Liverpool FC, one of the top teams in the Premier League, considered to be the best soccer league in the world, in 2017. Since then, an extensive amount of research has been done on his impacts on Liverpool's fan base and British society as a whole. The results are shocking: in 2018, hate crimes in Liverpool had decreased by 16% vs their expected value, and anti-Muslim tweets from Liverpool fans were a whopping 50% below expected (Alrababa'h et al., 2021). It is clear that parasocial contact is coming into play; it's unlikely that Salah had individual interactions with the thousands of fans that recognized the error of their ways.

Is the Salah case an outlier, or can other celebrities have the same levels of success in reducing prejudice? Through the literature I have been able to distill what I believe were the main determinants in Salah's breakthrough with Liverpool fans. The first, and most obvious, is his incredible ability on the soccer pitch. Salah won the Premier League's Golden Boot award for top goalscorer in the league in each of his first two seasons with Liverpool; the year after that, he led the team to a Premier League championship. He has been ranked among the 10 best footballers in the world every year since signing with Liverpool. In short, any soccer fan in the world would be thrilled to have him playing for their team.

In additions to Salah's achievements on the pitch, he has proven to be a charitable and accessible person in his daily life. He has donated millions of pounds to improve infrastructure and fight hunger in his hometown of Nagrig, Egypt and beyond. His £2.4 million donation to rebuild a hospital in Cairo made him one of the 10 most charitable celebrities in England in 2021, according to *The Times* (McCall, 2022). He is also known for being very fan-friendly and down to earth. In 2019, a fan famously ran into a pole chasing after Salah's car; Salah promptly came back to check on the superfan and take a picture with him, bloody nose and all (Jahangir, 2022).

As previously mentioned, Islamophobia has long been ingrained in British society, and nowhere is that more true than in Liverpool, the site of Britain's first mosque. According to John Belchum, a History professor at the University of Liverpool, religious and ethnic minorities have been historically excluded from doing business in the city center, despite Liverpool's location as a port city (OpenLearn, 2015). This has made Liverpool one of the least integrated cities in Britain, creating little space for interaction between white Christians and everyone else. In 2015, two Muslim Liverpool fans praying in a stairwell at a match were described as "disgraceful" by a twitter user.

Anglia Ruskin lecturer Dr. Solava Ibrahim told BBC news that Muslims have frequently being "linked to terrorist attacks or debates around women's subjugation" in British popular discourse, so comments like these were considered par for the course at the time (Jahangir, 2022).

Clearly, Liverpool was in need of a metaphorical kick in the butt, and Mohamed Salah was able to give it one. Because of Salah's status as a regional hero, Liverpool fans were more willing to accept all parts of him. After all, if he scores for your team in a big match, is it that big of a deal if he prays afterwards? Due to the powers of parasocial contact, Liverpool fans seem to have projected their positive feelings about Salah onto Muslims as a whole. What has resulted is a city that is more welcoming and accepting than ever before, and hopefully it stays that way long after Salah's tenure with Liverpool is over.

# 4 Analysis of Hate Crimes in Wisconsin

I will first test the parasocial contact hypothesis through an analysis of hate crimes trends in Wisconsin. A hate crime is a drastic act of prejudice, and is typically carried out by extreme bigots or in an environment where acts of prejudice are socially acceptable (Brax and Munthe, 2014). If Giannis has successfully changed attitudes towards Black people and immigrants, then hate crimes against those groups should decrease, either through changing the attitudes of extreme bigots or by making prejudice less socially acceptable overall.

## 4.1 Data and Research Design

To measure hate crimes, my main variable of interest, I use reported hate crimes data from the FBI Uniform Crime Reporting (UCR) database. These data run from 2005 to 2020, and includes all 50 states and DC with the exception of Hawaii. To avoid measuring hate crimes that Giannis may not have an effect on, I only use incidents classified as anti-Black, anti-national origin, or anti-multi-racial group in my analysis. Also, the Wisconsin hate crime reporting system allows users to report crimes that are not typically classified as hate crimes as such, like welfare fraud; thus, I am limiting my analysis to the offense types used in the California reporting system, which is considered to be the highest-quality in the nation. The offense types used are aggravated assault, simple assault, intimidation, robbery, destruction/damage/vandalism of property, arson, and burglary/breaking and entering.

After performing the above cleaning, I find that an average of 20.4 hate crimes that meet my criteria are reported per year in Wisconsin. The year-over-year trend can be seen compared to the US average in Figure 2.

To determine if Giannis has had a real impact on hate crime numbers, I am tasked with determining what hate crimes in Wisconsin *would* have looked like had he never joined the Bucks. To do so requires building a model to predict post-Giannis hate crimes (from 2014-2020), which can then be compared to what actually happened. Armed with Wisconsin data from the pre-treatment period, and data from the rest of the country in both the pre and post-periods, I will create this model using a Synthetic Controls (SC) setup akin to that used in Jones and Marinescu (2022). This model utilizes the Stata package synth, designed by Abadie, Diamond, and Hainmueller (2011). Synth will first generate predictions for pre-treatment hate crimes using patterns in the pre-treatment data, and do the same for post-treatment hate crimes using those same data. To do this, SC places weights on each predictor (states, in this case) to determine its importance in the model. Treatment effects can then be estimated for each year by taking the difference between observed hate crimes and the estimated counterfactual.

**Yearly Hate Crimes in Wisconsin and the US**

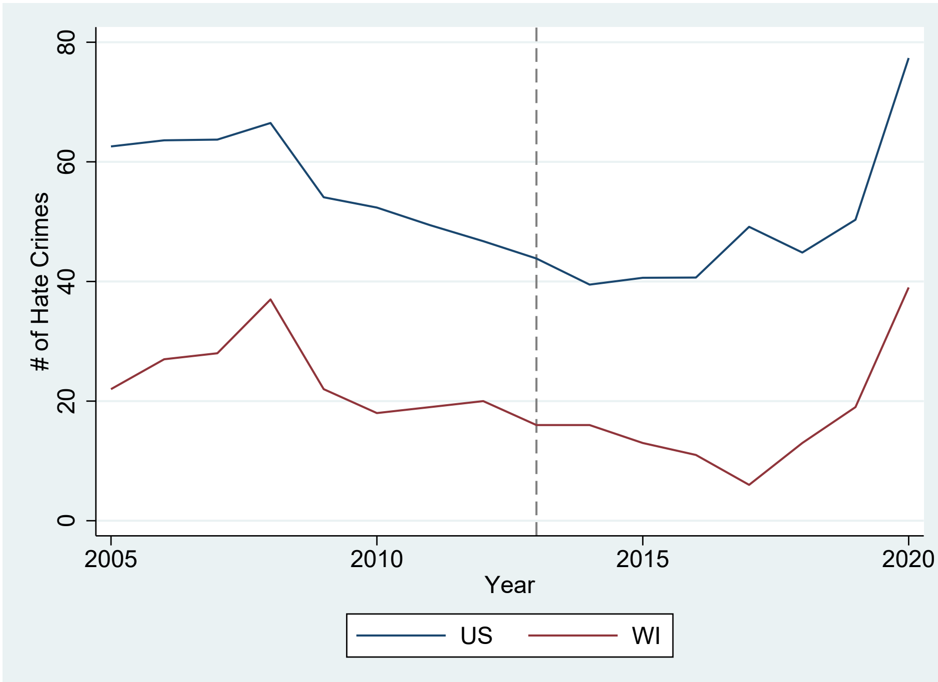



Figure 2: Hate crimes in WI and the US from 2005-2020. The dotted line marks 2013, the year Giannis is drafted.

A synthetic control model alone is not sufficient evidence to show a relationship. While it is a useful tool for demonstrating unexpected patterns in the data, its use of a single treated unit renders standard statistical inference unusable (Hahn and Shi, 2017). As a robustness check and a supplement to the SC model, I will implement a Synthetic Difference-in-Differences model (SDID), as developed for Stata by Arkhangelsky et al. (2021). SDID combines the strengths of Difference-in-Differences (DID) and SC approaches: it allows for the control and treatment groups to trend on different levels (a characteristic of DID), while synthetically generating the control unit to lessen the need for parallel trends (Clarke et al., 2023). Another benefit of SDID estimation is the ability to test for statistical significance. While I am still using a single treated unit, permutation tests can be generated by specifying the *placebo* inference method within SDID. In the following models, I use 100 placebo replications to estimate average treatment effects and construct confidence intervals.

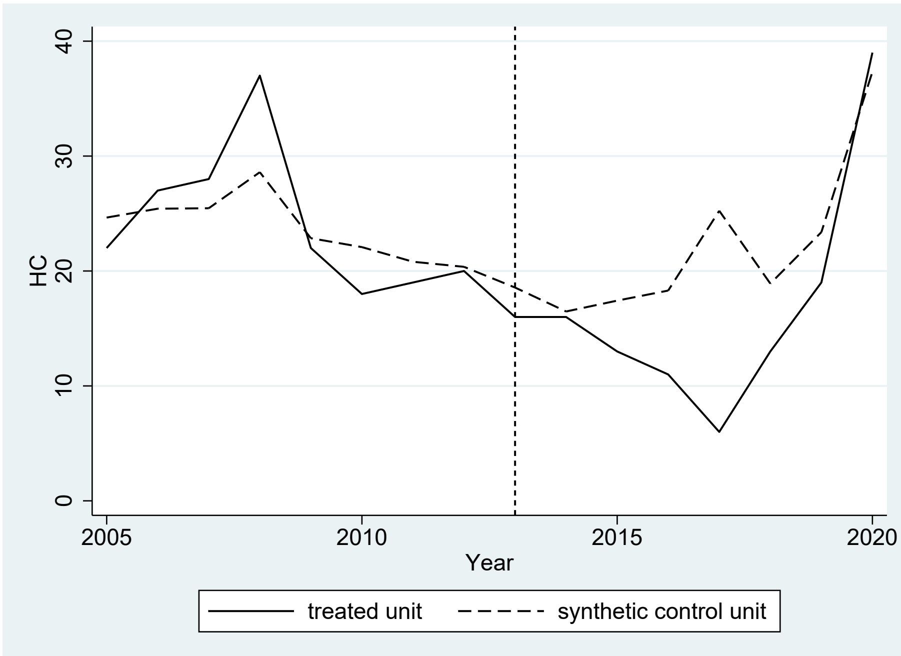
## 4.2 Results

My main results can be found in Figure 3. Plot (a) shows observed hate crimes in Wisconsin compared to its estimated counterfactual. Plot (b) shows this observed vs predicted comparison for 46 states, a result of zero meaning that observed and predicted hate crimes were the same in that year. In both plots, the treatment period begins in 2013, the year that Giannis is drafted by the Bucks. A discussion of predictor weights in regards to this model can be found in Section 7.2 of this paper.

To ensure that the synthetic control model is functioning properly, the difference between predicted and observed hate crime statistics in the pre-treatment period should be relatively small. In plot (a), it is clear that while predicted and observed hate crimes are not a perfect match, they follow similar trends, though the observed values are more volatile. In this period, the average difference between the two is 0.35, meaning that 0.35 more hate crimes are occurring per year than than the model predicts. The post-treatment period, however, is a different story. The observed unit experiences a clear diversion from the counterfactual starting in 2015, though the gap closes again in 2020. I estimate the average treatment effect from 2014-2020 to be -5.72, which corresponds to a 34% drop in hate crimes vs expected. This estimate has an RMSPE (Root Mean Squared Prediction Error) of 3.61, from which I can construct a 95% confidence interval of [-2.11, -9.33] for the estimated treatment effect.

Plot (b) shows how trends in Wisconsin's reported hate crimes compare to those of other states. It appears that Wisconsin was around average in the pre-treatment period, and was within or near the bottom quartile from 2015-2018. The y-axis of this plot is measured in difference in the raw number of hate crimes instead of percent difference, as states with a low volume of reported hate crimes create a host of problems for the percent difference model. For one, they will have high variability in their treatment effect (for example, a state reporting an average of 6 incidents that sees 1 reported incident in a given period appears to have a massive decrease in hate crimes); and if there are 0 reported hate crimes for a period, the percent difference cannot be measured at all (as was the case in Alabama in 2017 and 2018). The reporting issues associated with hate crimes will be discussed further on in this paper.

**(a) Observed vs Predicted Hate Crimes in Wisconsin**




**(b) Observed vs Predicted Hate Crimes in All States**

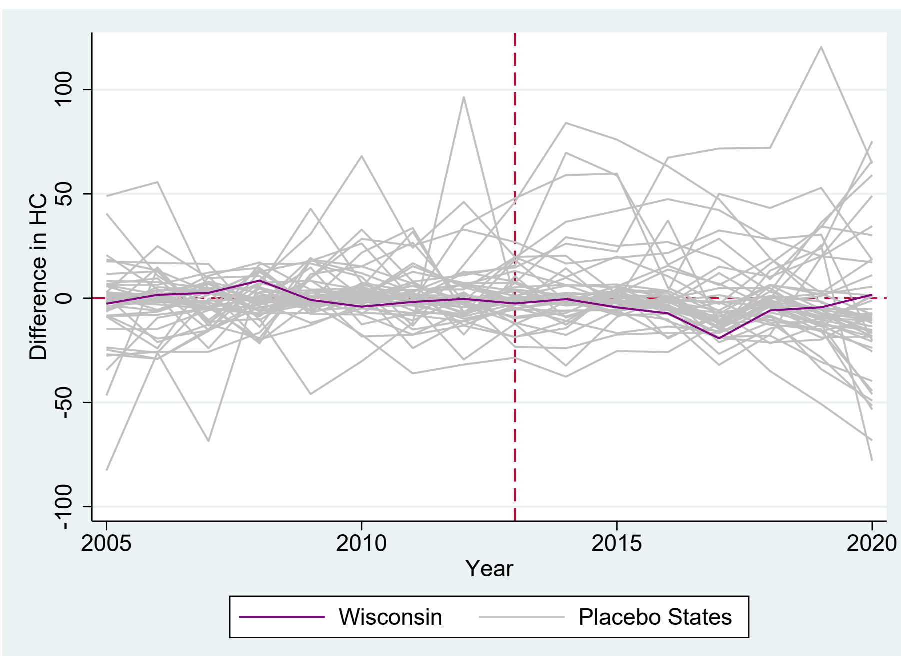
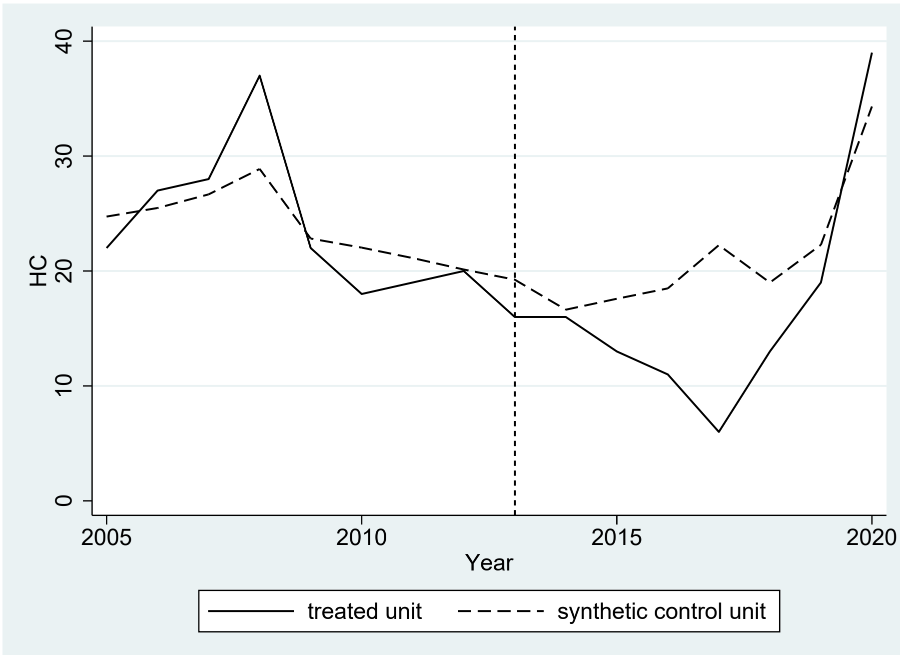



Figure 3: Results from synthetic control analysis. Note that California and New Jersey are excluded from plot (b), as their high volume of reported hate crimes led to variability in the hundreds (in the positive direction) for the estimated treatment effect.

To improve the reliability of this analysis, I then added controls for unemployment rate and median income, both of which are determinants of crime overall. The results of this analysis can be found in Figure 4. Little changes occur to the model with the addition of these controls. The average difference between synthetic and observed in pre-treatment drops from 0.35 to 0.14, indicating an improvement in the model's predictive ability. The average treatment effect post-Giannis also drops from -5.72 to -4.79, still a 30.7% reduction from expected levels. With a new RMSPE of 3.48, a confidence interval can be constructed from [-1.31, -8.27].

These controls help explain a good deal of the variation in the data, particularly in years with increased hate crimes. Two of the biggest spikes in the data, both in Wisconsin and nationwide, occur in 2008 and 2020. Both of these spikes occurred in a recession year, which corresponds to higher unemployment and lower median income; I would thus expect to see an increase in all types of crime in these years. By far the largest spike occurs in 2020, which is the only year post-treatment that Wisconsin's estimated treatment effect is positive. This can likely be explained by a combination of COVID and the racial strife that occurred in summer of 2020. In Wisconsin, Kyle Rittenhouse's rampage through Kenosha following the shooting of Jacob Blake prompted a visit from then-president Donald Trump, at which Rittenhouse supporters called the 17-year-old "a hero" and "a patriot", according to interviews done by Politico (Korecki and Cadelago, 2020). Rittenhouse clearly empowered extreme bigots to feel that they could get away with heinous acts of violence as long as"self-defense" was in play, which I argue helps explain Wisconsin's explosion in reported hate crimes in 2020.

**(a) Observed vs Predicted Hate Crimes in Wisconsin w/ controls**




**(b) Observed vs Predicted Hate Crimes in All States w/ controls**

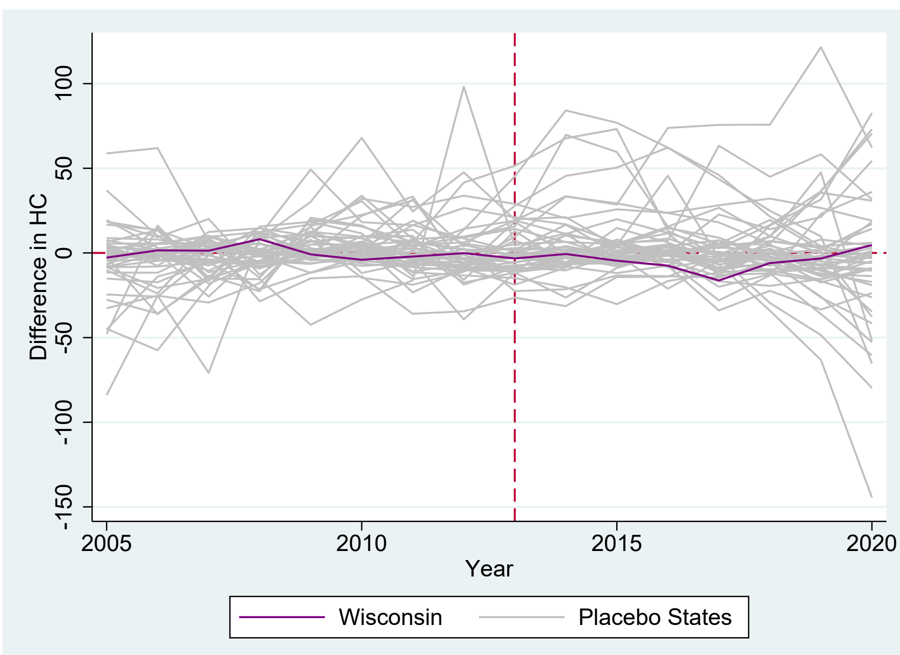



Figure 4: Results from synthetic control analysis with the addition of median income and unemployment as control variables.

I then implement a SDID approach using the same data and controls as outlined above. I also add a second treatment, Giannis's first All-Star selection, to account for his rise in popularity and performance. Just his mere existence will not change attitudes; he must be playing well, and people must be taking note of his play and his off-court actions. To test my concerns about 2020 washing out results, I generate the same models without the year 2020 in the dataset. Figure 5 shows SDID analyses with a full data panel, while Appendix A shows the models excluding 2020; the statistical results for all 4 models can be found in Table 1.

Similar trends can be seen in the treatment and control groups as in the SC analysis, most notably with large gap between the treatment and control groups in 2017. However, Model (a)'s 2013 treatment yields an estimated effect of -0.32 and a t-statistic of -0.01 making it impossible to argue that there is any sort of effect occurring. While changing the treatment introduction to 2016 leads to a larger treatment effect (-4.7), these results are still far from statistically significant. Little changes when 2020 is dropped from the dataset: the draft treatment coefficient flips from slightly negative to slightly positive, but otherwise these results further reinforce a lack of significance.

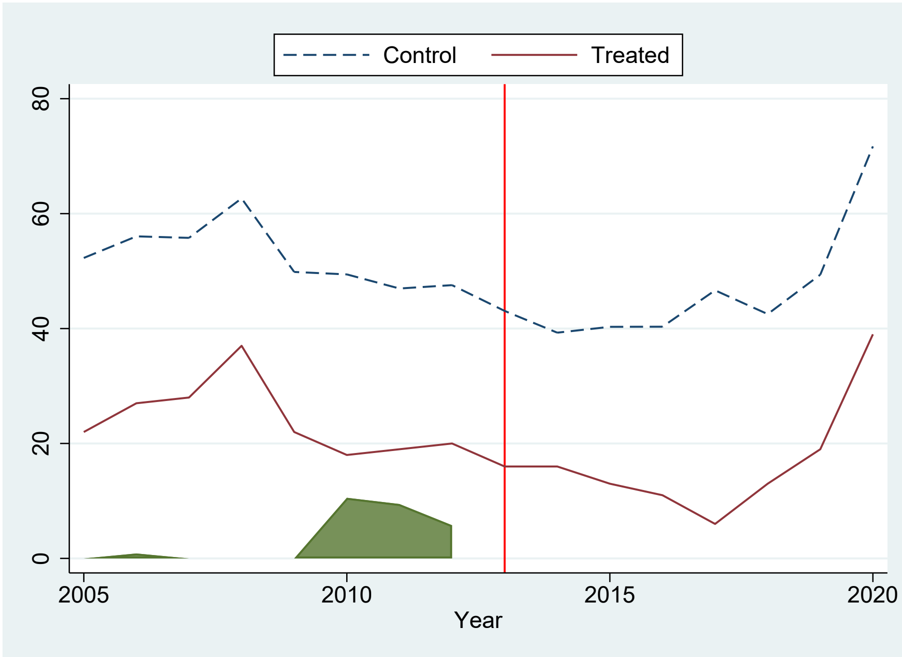
Table 1: Hate Crimes SDID Results

| | (1) Since Drafted | (2) Since First All-Star | (3) Draft - No 2020 | (4) All-Star - No 2020 |
|---|---|---|---|---|
| treated | -0.320 | -4.709 | 0.205 | -4.258 |
| | (-0.01) | (-0.18) | (0.01) | (-0.23) |
| Observations | 800 | 800 | 750 | 750 |

$t$ statistics in parentheses

$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

(a) **HC in WI vs Expected: SDID, Draft Treatment**




(b) **HC in WI vs Expected: SDID, All-Star Treatment**

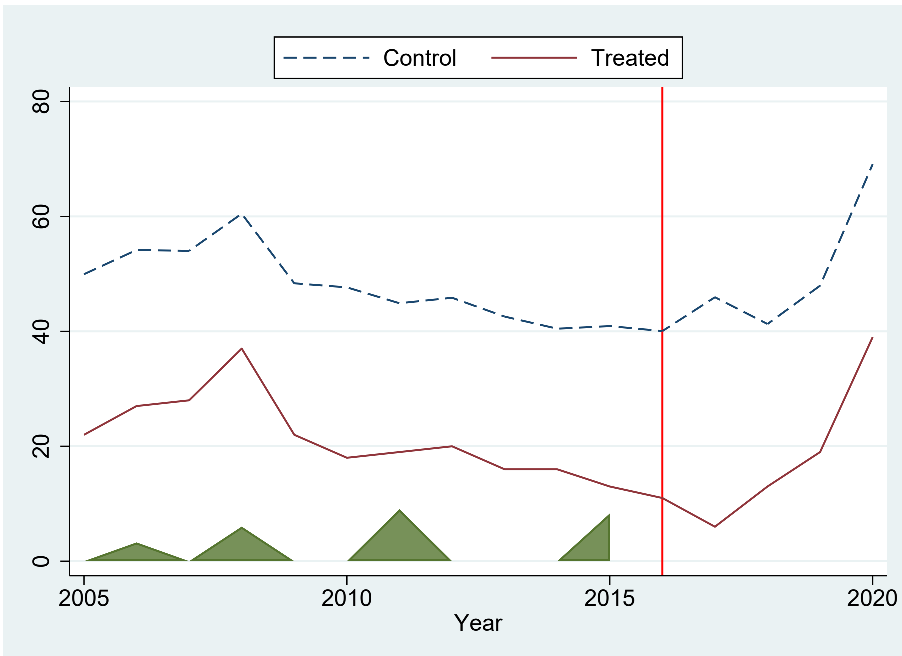



Figure 5: Results from SDID model with WI as the treatment and the rest of the US as the control group.

There are several controls that could be added to strengthen this analysis, the first being race, age and gender state-level demographics. Males ages 16-24 are more likely to commit crimes than any other group, and this is especially true for hate crimes, where the majority of incidents are perpetrated by young men "looking for some fun" (McDevitt et al., 2002). As for racial demographics, if few Black people live in a state, it is intuitive that comparatively few anti-Black hate crimes will occur. Another necessary control is police reporting quality. There is massive variation in the number of hate crimes reported per state (in 2018, for instance, California reported 340 hate crimes that met my criteria, while Mississippi reported 0), though there is much less variation in individual states over time. There are a number of online data sources that compare reported crimes to estimated actual crimes in each state, which could help make sense of the gulf in reporting between states.

Another potential robustness test involves a comparison of other crime types in Wisconsin, which can be collected from the FBI UCR database. If reported hate crimes are dropping, but other offense types are dropping at the same time, it would be difficult to argue that Wisconsin is seeing a decline specifically in bias-motivated crimes, which is the case I am trying to make. A glance at the data shows that violent crime types have steadily increased in Wisconsin since 2005, while property crimes have steadily decreased. Given that most hate crimes are classified as violent crimes (84%, according to the US Department of Justice), this seems to match my hypothesis that hate crimes in Wisconsin are declining independent of trends in other crime types.

## 5 Google Trends Analysis

Hate crimes are not the way to measure trends in racial bias over time. While they can serve as a marker for the social acceptability of racist acts, hate crimes more so reflect the sentiments of extreme bigots than those of the general population. Google searches, on the other hand, reflect more privately held sentiments. Oftentimes, people search for terms and phrases that they wouldn't even say aloud to close friends or family (Davidowitz, 2017), which differentiates Google searches from less extreme, but still public, declarations of bias like racist tweets or Facebook posts. Thus, if you can find a word or phrase that only people holding a certain bias would use, you can very accurately measure trends in that bias. Unfortunately, no such perfect measure exists. Most every word has several different meanings, so it can be difficult to claim that all searches for a term like "alien" are indicative of anti-immigrant bias, when in reality many of those searches are related to space aliens. If the search is narrowed to "illegal aliens", which would deal with other confounding meanings of the word alien, there is not enough search frequency at the state level to generate results for every period. The challenge, then, is to find language that is commonly searched that still conveys clear bias.

## 5.1 Data and Research Design

My first objective is to analyze trends in the use of anti-immigrant language in Wisconsin Google searches. My prediction is that the emergence of Giannis has made Bucks fans more sympathetic towards immigrants, and undocumented immigrants in particular. I will be using the Google Trends tool provided by Google for this analysis. Google Trends allows the user to type in any word or phrase that others might search, and returns the relative frequency (on a scale of 0 to 100) of the use of that term for numerous periods within a specified time frame. This data can be collected at anywhere from metro-level to world-level; the broader your scope, the less targeted your findings, and the narrower you go the harder it is to obtain reliable data. Ideally, I would be able to use the Milwaukee metro area for this analysis in addition to a state-level setup, as Google search interest in Giannis and the Bucks is around twice as as concentrated there as in other parts of the state. Unfortunately, none of the terms or phrases I have looked at are searched enough in Milwaukee alone to generate a frequency value for most periods.

After some deliberation, I elected to first use the phrase "illegal immigrants" to measure anti-immigrant bias. This phrase is frequently used within searches such as "Do illegal immigrants get free healthcare", "How much do illegal immigrants cost the US", and "How many illegal immigrants voted", which I argue are a direct result of right-wing media propagation and the sentiments of conservative leaders like Trump. Of course, some individuals may be earnestly searching for information about undocumented immigrants in an unbiased way, just without knowledge of the appropriate language to use; this will be the case with almost any search term I could use. However, I would argue that the searches I outlined above were more than likely made by individuals holding some degree of prejudice against undocumented immigrants, making "illegal immigrants" an effective proxy for anti-immigrant bias levels.

The data I've elected to use covers 5 states: Wisconsin will make up the treatment group, and its neighboring states with NBA teams—Minnesota, Michigan, Illinois, and Indiana—as the control group. These control states are similar to Wisconsin culturally and in terms of their levels of Black-white segregation (Austin, 2020), but none have had a superstar like Giannis, who is uniquely suited to create positive parasocial contact, to rally around. The data follows these states from January 2010 to November 2022 and is collected monthly.

I implement another set of SDID analyses to test for changes in anti-immigrant sentiment in Wisconsin. I introduce three different treatments: the first occurs when Giannis is drafted (June 2013), the second when he makes his first appearance in the All-Star Game (February 2016), and the third when he wins his first MVP award (June 2019).

## 5.2 Results

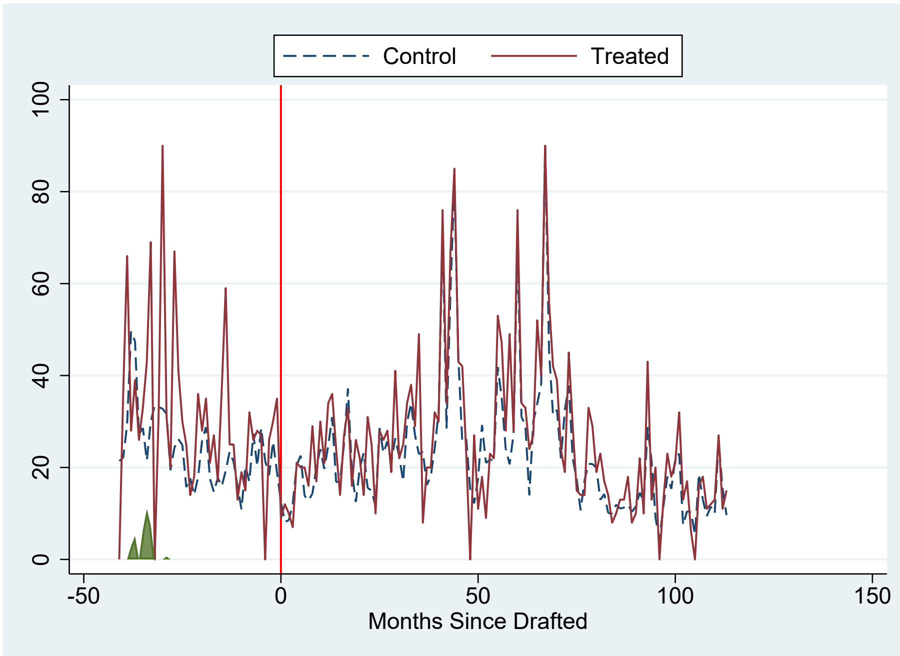
My main results from this analysis can be found in Figure 6 and Table 2. The y-axis of the in models Figure 6 measures level of prejudice (as according to Google Trends data), as mentioned previously, on a scale of 0 to 100. All three models yield statistically significant results demonstrating a decline in anti-immigrant sentiment as compared to the control group. Looking at Figure 6a, this trend is made clear. Prior to treatment, Wisconsin experiences a number of spikes in anti-immigrant searches that are not matched by the control group. After treatment, however, trends in the treatment data are matched much more closely by the control data; a similar effect can be seen in Figures 6b and 6c as well. Thus, the effect we are seeing is Wisconsin's prejudice levels becoming more comparable with those of its peer states, when they were previously much higher. As one might expect, this effect grows as Giannis and the Bucks improve and garner more attention: A 16% reduction occurs after Giannis is drafted, a 19% reduction after his first All-Star appearance, and a 21% reduction after winning his first MVP.

Table 2: Google Trends SDID Results

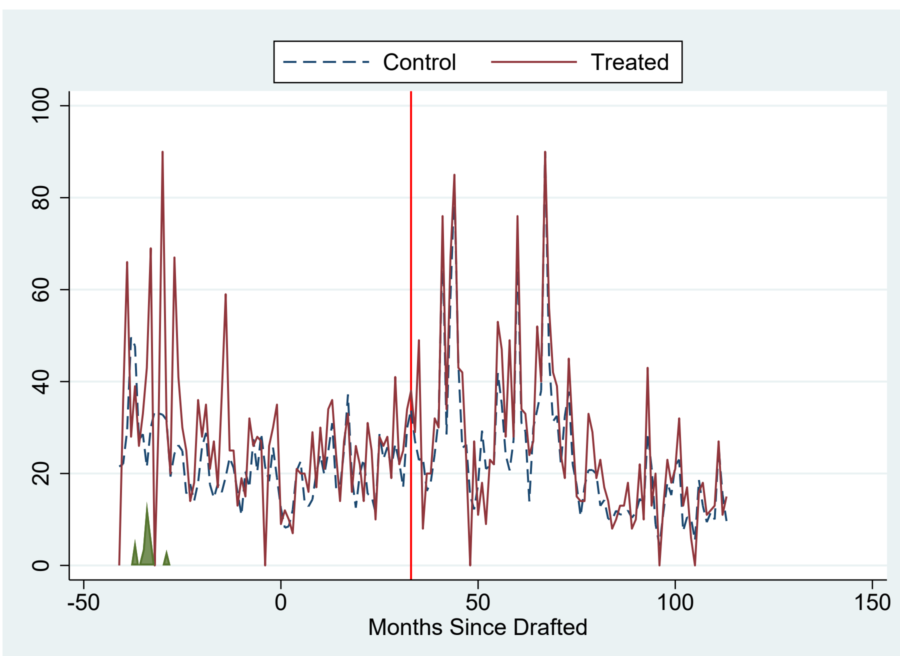
| | (1) Since Drafted | (2) Since First All-Star | (3) Since First MVP |
|---|---|---|---|
| Treated | -10.42$^{***}$ | -12.80$^{**}$ | -13.78$^{***}$ |
| | (-17.75) | (-2.92) | (-4.75) |
| Observations | 775 | 775 | 775 |

$t$ statistics in parentheses
$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

(a) **Google Trends SDID: Drafted Treatment**




(b) **Google Trends SDID: All-Star Treatment**



**(c) Google Trends SDID: MVP Treatment**

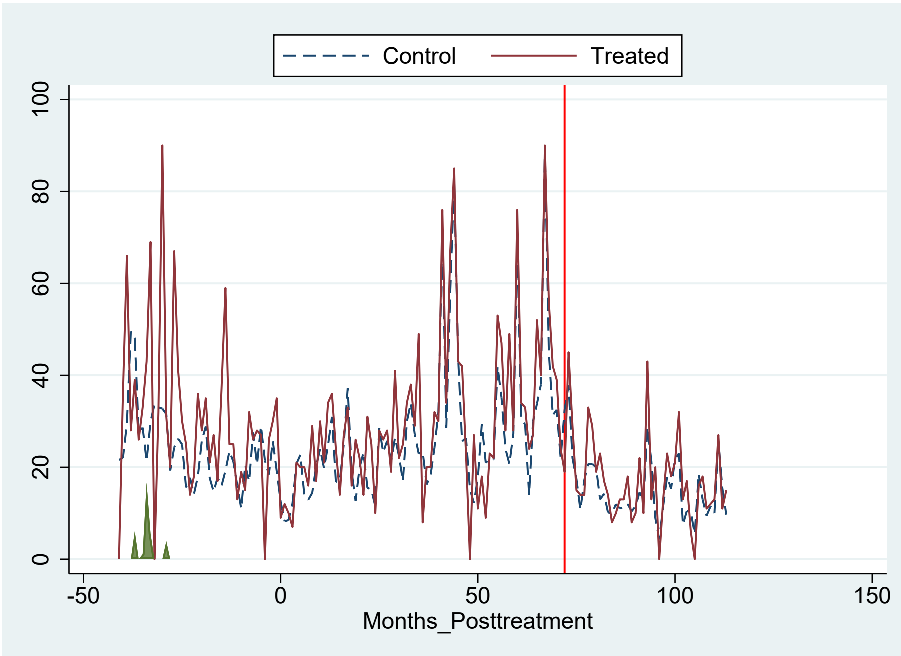



Figure 6: Results from Google Trends analysis, 1/2010 - 11/2022

# 6 Discussion

Overall, the results of these two analyses demonstrate the effect of the parasocial contact hypothesis. Exposure to Giannis Antetokounmpo over the course of several years has likely reduced bias towards immigrant populations in Wisconsin, and while no statistically significant results were found in the hate crimes analysis, a visual reduction does occur after treatment. Why do I find a statistically significant reduction in anti-immigrant sentiment, but not in hate crimes, the majority of which are categorized as anti-Black in my dataset? There are a few potential reasons for this; the first is the poor quality of the hate crimes data, which I will discuss further in Section 6. The second is that in the NBA, being Black is not a unique identity, but growing up as an undocumented immigrant is. If Giannis is driving these results as I hypothesize, it seems that the "novelty" of his upbringing and subsequent immigration to the US is creating the most substantial changes in peoples' biases.

It is easy to get excited about significant results, but it is also important to remember the difference between correlation vs causation in a study of this nature. I am not claiming that all of the reduction in anti-immigrant sentiment in Wisconsin is a result of Giannis; there are many other events or people that could have impacts on prejudice levels in the state. The 2020 hate crimes data are a great example of this, as any impact that Giannis may have had is completely washed out by major events like COVID. It is, however, very surprising that a politically polarized state like Wisconsin is seemingly becoming less racist as compared to its neighbors. As I have outlined above, Giannis's unique characteristics make his presence a plausible explanation for this improvement.

While parasocial contact has been shown to be a force for positive change in the case of Giannis and Salah, negative events or media portrayals can lead to an increase in bias through the same mechanisms. In August 2021, England lost the Euro Cup, a soccer tournament amongst all European nations, in a penalty kick shootout. All three of their PK misses came from young Black players: Marcus Rashford, Jadon Sancho, and Bukayo Saka. Within 24 hours of the end of the match, Twitter had removed over 1,600 that contained racist abuse towards one or more of these men, the vast majority of which were sent from within the UK (Twitter UK, 2021). It seems as though many fans will project their feelings about a player onto the outgroup(s) the player identifies with regardless of whether those feelings are positive or negative. For most professional athletes, this burden of social responsibility is likely far beyond what they signed up for.

Though the findings would likely be far less pleasant than those of my study, a follow-up study on an event like Euro 2020 would make for another useful test of the parasocial contact hypothesis. What made Giannis and Salah so successful in changing attitudes was their combination of sustained success in sport and positive portrayal in the media. A missed PK in a high-stakes situation, though, is clearly enough to wipe out any goodwill a player has with their fans or the press. What remains unknown is whether a shock like what I have described would create a permanent change in attitudes or simply a temporary one.

# 7 Limitations

## 7.1 Hate Crimes Data

The biggest source of potential error in this paper comes from the FBI UCR hate crimes data. According to Sandholtz et al. (2013), around 7,000 individuals were victimized in the 6,200 hate crimes that were reported to the FBI in 2013. In that same year, the Bureau of Justice Statistics found that more than 250,000 Americans were victimized in hate crimes every year from 2003 to 2011, using results from the National Crime Victimization Survey (NCVS). That means that less than 3% of hate crimes are reported to the FBI on an annual basis.

What is to blame for the sorry state of the UCR data? For one, the majority of hate crimes are never reported directly to law enforcement agencies. Oftentimes, hate crime victims from marginalized communities do not report because they think the police won't be helpful (Sandholtz et al., 2013). That sentiment is well-backed by evidence: from 2007-2011, only 4% of hate crimes reported to police resulted in arrests (Sandholtz et al., 2013).

Even if all hate crimes were reported to the police, not all of them would show up in the UCR database. The UCR is a voluntary reporting system, and not all agencies make use of its hate crimes branch, the Hate Crimes Statistics Program. According to the FBI, 87% of agencies did not report a single hate crime in 2013. Many agencies are reluctant to report for fear of tarnishing the reputation of their city, as per Northeastern's director of the Institute on Race and Justice Jack McDevitt. Many officers are not trained to properly identify hate crimes, and language and cultural barriers often stand in the way of proper classification.

All of these factors combine to create a database that is relatively unreliable and inconsistent across states. Unfortunately, the UCR system is also the only source for nationwide hate crime statistics in the US. The NCVS is a representative survey of 90,000 households, and though it is considered to be very accurate it cannot be applied to the type of study I am conducting. Local sources of hate crime data have proven to be more reliable than the UCR, but collecting that data at my level of analysis was beyond the scope of this project.

However, new initiatives may improve reporting on bias-motivated incidents in the near future. A new bill in the Minnesota State Legislature would allow community organizations to work with the MN Department of Human Rights to compile and report data on hate *incidents*, acts that are harmful and clearly bias-motivated but do not necessarily constitute a crime. If passed, this bill would take the police out of the equation, addressing both victims' unwillingness to report to police and the unwillingness of many agencies to report to the UCR database. If legislation like this proliferates in the US, future research on hate incidents could be improved substantially.

### 7.2 Synthetic Control Analysis

While my synthetic control models did an excellent job of predicting pre-treatment hate crimes, particularly for Wisconsin, there are still some inexplicable quirks in the results. Synth assigns weights to predictors-in this case, states-based on their similarity to the treatment group. The states that were weighted highly in the models seems to be relatively random: in the no-controls model, Mississippi accounts for over a third of the total weight, and in the model with controls Mississippi and Alaska accounted for more than 10% each. These states are extremely low-reporting, as both averaged less than 3 anti-Black or anti-immigrant hate crimes reported to the FBI from 2005-2020. My biggest concern with this was the 25% spike in projected counterfactual hate crimes from 2016 to 2017 in Wisconsin, as Mississippi saw a jump from 0 to 13 hate crimes in that same period that could have skewed the model. Fortunately, a follow-up analysis with Minnesota as the treatment state yielded the same predicted spike in 2017, even though Mississippi and Alaska accounted each accounted for about 2% of the total weight. This seems to indicate that there was a nationwide spike in hate crimes in 2017, not just in one or two states. The Minnesota synthetic control plot can be found in Figure 7. This does not mean, though, that treatment effects in other years were not disproportionately impacted by the model's choice of weights.

**Observed vs Predicted Hate Crimes in Minnesota**

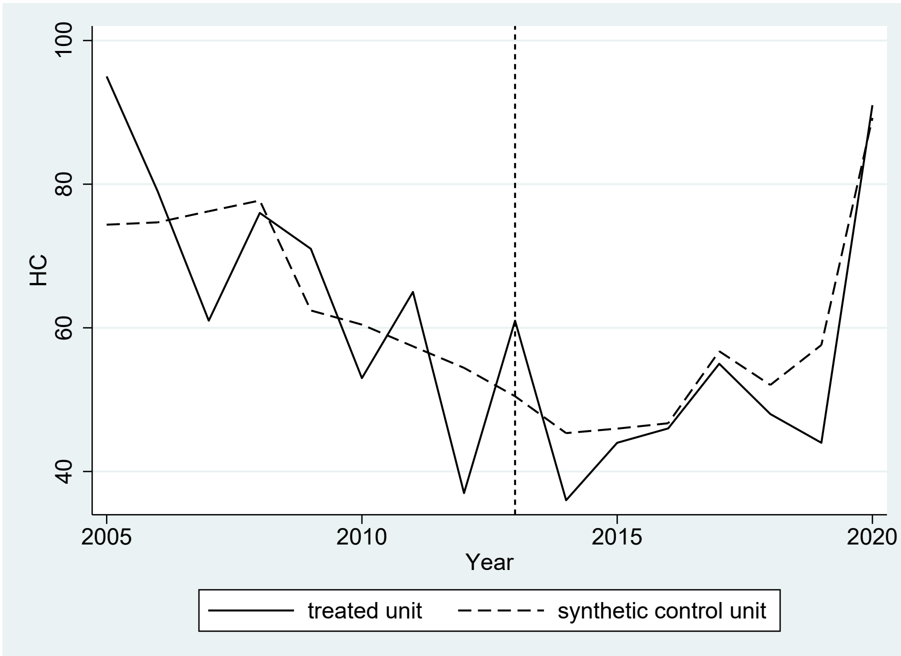



Figure 7: Results from synthetic control analysis of Minnesota hate crimes. Minnesota sees a spike in reported hate crimes in 2017 consistent with the national trend, which is not the case in Wisconsin.

There are also a few seemingly errant predictions made by the model when analyzing states other than Wisconsin. The most striking instance of this comes from Washington state in 2020. 188 anti-Black or anti-immigrant hate crimes were reported, but the model predicted there would be 332.5, resulting in an estimated treatment effect of -144.5. While Washington did not see the spike in hate crimes that most states did in 2020, 188 was still their second highest reported value since 2005, behind the 196 they reported in 2019. This level of volatility was unexpected from an otherwise conservative model, but given that numerous states reported nearly 100% spikes in hate crimes in 2020 (Wisconsin being among them), I can see why synth would have predicted this. With higher quantities of data, these issues would likely be much less prevalent, which goes back to the faults of the UCR database.

### 7.3 Google Trends Analysis

As I touched on earlier in this paper, selecting the right search terms for a Google Trends analysis is quite challenging and subjective. What I may view as problematic language indicative of bias, another person with the same information may not. There has been a good deal of scholarship using Google data to measure anti-Black and anti-Muslim sentiment, much of it carried out by data scientist Seth Stephens-Davidowitz. However, no other literature that I am aware of attempts to measure Anti-Immigrant bias with Google data, so the framework I have set up for that portion of the analysis is entirely my own. This opens the door for criticism that could not be levied as easily had I used the search terms of another well-regarded study.

The other issue that comes with Google Trends data is that it is constantly updating due to its setup as a relative frequency graph. If a term blows up online today, it will impact the relative frequency in every period that came before it. This means that the data that I first pulled on November 26th, 2022 looks different than the data available today, and that will look different than the data available a week from now.

## 8 Conclusion

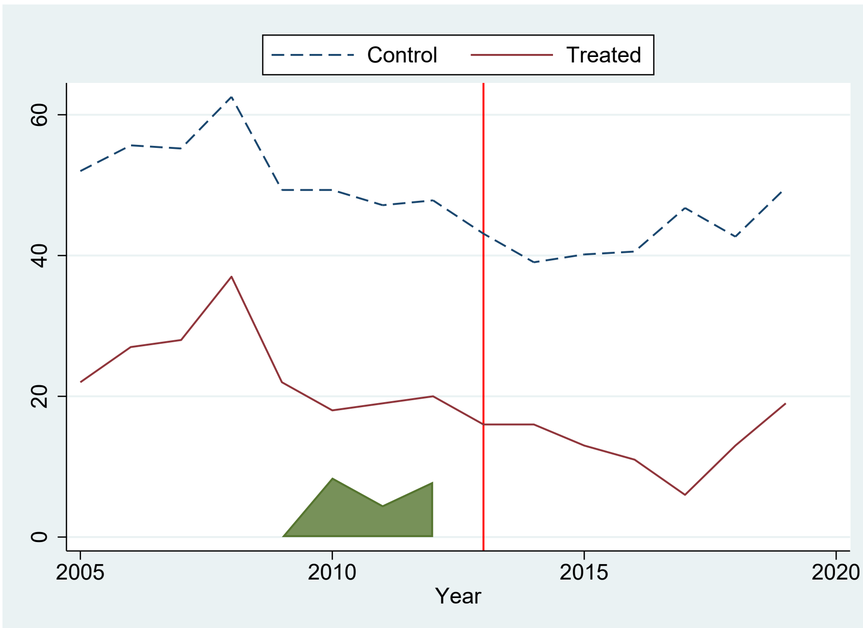
This paper was designed to show the parasocial contact hypothesis at work, and how it can lead to positive societal outcomes. Giannis Antetokounmpo makes for a near-perfect subject for this study: he is an incredible basketball player and a likeable figure, competing for a city where inter-group interactions have historically occurred much less frequently than they should. I find no statistically significant change in the frequency of anti-Black and anti-immigrant hate crimes after Giannis joined the Bucks; though my Synthetic Control analysis appears to show a reduction, any significance is likely washed out by the spike in hate crimes in WI in 2020. I do, however, estimate a 16% reduction in anti-immigrant Google searches after June of 2013; that effect jumps to 19% after Giannis makes his first All-Star game in 2016, and to 21% after he wins his first MVP. While there is still more to be done to create the most credible analyses I am capable of, these results are quite encouraging and demonstrate the impact Giannis has had on the city of Milwaukee and his fans all over Wisconsin.

There are ample opportunities for future research using this study as a starting point. There were a few methods of analysis used by Alrababa'h et al. (2021) in their breakthrough study on Mohamed Salah that I was unable to implement in my own work. The first was analysis of public opinion surveys, for which I could find no suitable data. The other, and one that I would have strongly considered if not for time constraints, was the use of Twitter scraping to determine trends in anti-Muslim tweets before and after Salah joined Liverpool. Social media posts demonstrate an intermediary level of bias between Google searches and hate crimes: they can still be public declarations of prejudice, but without the physical harm caused by an in-person crime. This analysis is where the most profound results of the Salah study were found, which tracks with what we know about human behavior. Extreme bigots are unlikely to have their minds entirely changed by the outcome of a soccer game, and people's public behaviors don't usually match their private ones(Stephens-Davidowitz, 2017); just because someone stops tweeting racist things doesn't mean they've stopped searching Google for racist things. What a powerful figure like Giannis or Salah can do is move the needle of public consciousness and change what is socially acceptable in everyday interactions, which is what makes Twitter analysis such a powerful tool in studying parasocial contact. The methods I have used as well as those outlined in this section could be applied to other stars in the NBA, such as Cameroonian center Joel Embiid of the Philadelphia 76ers, or to other athletes around the world.

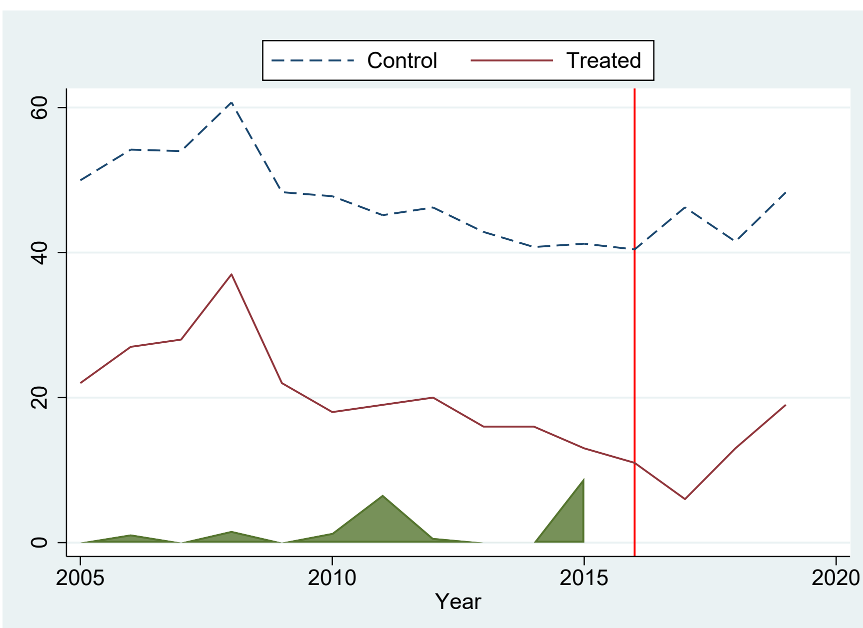
# Appendices

Appendix A: Hate Crime SDID models - 2020 excluded

**(a) HC SDID: Drafted Treatment, No 2020**




**(b) HC SDID: All-Star Treatment, No 2020**



## References

Alrababah, Ala, William Marble, Salma Mousa, and Alexandra Siegel. 2019. "Can Exposure to Celebrities Reduce Prejudice? The Effect of Mohamed Salah on Islamophobic Behaviors and Attitudes." SocArXiv. https://doi.org/10.31235/osf.io/eq8ca.

Arkhangelsky, Dmitry, Susan Athey, David A. Hirshberg, Guido W. Imbens, and Stefan Wager. 2021. "Synthetic Difference-in-Differences." American Economic Review 111 (12): 4088–4118. https://doi.org/10.1257/aer.20190159.

Austin, John C. 2020. "COVID-19 Is Turning the Midwest's Long Legacy of Segregation Deadly." Brookings (blog). April 17, 2020. https://www.brookings.edu/blog/the-avenue/2020/04/17/covid-19-is-turning-the-midwests-long-legacy-of-segregation-deadly/.

"Before The Windrush: How Did Liverpool Become Such a Poorly-Integrated City?" n.d. Before The Windrush: How Did Liverpool Become Such a Poorly-Integrated City? Accessed December 22, 2022. https://www.open.edu/openlearn/history-the-arts/history/social-economic-history/history-the-arts/history/social-economic-history/the-windrush-how-did-liverpool-become-such-poorly-integrated-city.

Brax, David, and Christian Munthe. 2015. "The Philosophical Aspects of Hate Crime and Hate Crime Legislation: Introducing the Special Section on the Philosophy of Hate Crime." Journal of Interpersonal Violence 30 (10): 1687–95. https://doi.org/10.1177/0886260514555374.

Chetty, Raj, Nathaniel Hendren, Maggie R Jones, and Sonya R Porter. 2020. "Race and Economic Opportunity in the United States: An Intergenerational Perspective*." The Quarterly Journal of Economics 135 (2): 711–83. https://doi.org/10.1093/qje/qjz042.

Clarke, Damian, Daniel Pailañir, Susan Athey, and Guido Imbens. 2023. "Synthetic Difference In Differences Estimation." arXiv. http://arxiv.org/abs/2301.11859.

“Combatting Online Racist Abuse: An Update Following the Euros.” n.d. Twitter UK. Accessed December 20, 2022. https://blog.twitter.com/en_gb/topics/company/2020/combatting-online-racist-abuse-an-update-following-the-euros.

Enos, Ryan D. 2017. The Space between Us: Social Geography and Politics. Cambridge: Cambridge University Press. https://doi.org/10.1017/9781108354943.

Findling, Mary, Robert J. Blendon, John Benson, and Howard Koh. n.d. “COVID-19 Has Driven Racism And Violence Against Asian Americans: Perspectives From 12 National Polls.” Health Affairs Forefront. Accessed December 20, 2022. https://doi.org/10.1377/forefront.20220411.655787.

Hahn, Jinyong, and Ruoyao Shi. 2017. “Synthetic Control and Inference.” Econometrics 5 (4): 52. https://doi.org/10.3390/econometrics5040052.

Jackson, Chris, Jennifer Berg, and Jinhee Yi. 2020. “New Center for Public Integrity/Ipsos Poll Finds Most Americans Say the Coronavirus Pandemic Is a Natural Disaster.” Ipsos. April 28, 2020. https://www.ipsos.com/en-us/news-polls/center-for-public-integrity-poll-2020.

Jahangir, Rumeana. 2022. “Mohamed Salah: Why New Liverpool Deal Goes beyond Football.” BBC News, July 2, 2022, sec. Liverpool. https://www.bbc.com/news/uk-england-merseyside-59622430. Jarvie, Grant. 2019. “Mo Salah Changing Social and Political Attitudes: Some Liverpool Voices.” Sport Matters. August 31, 2019. https://www.blogs.hss.ed.ac.uk/sport-matters/2019/08/31/mo-salah-changing-social-and-political-attitudes-some-liverpool-voices/.

Jones, Janine M. 2021. “The Dual Pandemics of COVID-19 and Systemic Racism: Navigating Our Path Forward.” School Psychology (Washington, D.C.) 36 (5): 427–31. https://doi.org/10.1037/spq0000472.

Korecki, Natasha, and Christopher Cadelago. n.d. “With a Hand from Trump, the Right Makes

Rittenhouse a Cause Célèbre.” Politico. Accessed December 20, 2022. https://www.politico.com/news/2020/09/01/trump-rittenhouse-kenosha-support-407106.

Kraemer, Sam. 2021. “NBA Finals: Deer District Shines Years after Development Doubts.” Text.Article. FOX6 News Milwaukee. FOX6 News Milwaukee, Wisconsin & Local Milwaukee News WITI. July 15, 2021. https://www.fox6now.com/sports/bucks-deer-district-history.

Levin, Brian. n.d. “Report to the Nation: 2020s - Dawn of a Decade of Rising Hate.” Accessed December 20, 2022. https://www.csusb.edu/sites/default/files/2022-08/Report%20To%20The%20Nation8-4-22.pdf.

Logan, John. n.d. “Diversity and Disparities: Racial Segregation Data.” Accessed April 16, 2023. https://s4.ad.brown.edu/projects/diversity/segregation2020/Default.aspx.

Luthern, Ashley, and Andrew Mollica. n.d. “How We Measure Segregation and What the Numbers Actually Tell Us.” Journal Sentinel. Accessed April 16, 2023. https://www.jsonline.com/story/news/special-reports/milwaukee-violence/2019/07/10/milwaukee-segregation-how-we-measure-and-define/1523075001/.

McCall, Nick Rodrigues and Alastair. 2022. “First They Made Their Fortunes. Now They’re Giving Them Away,” May 20, 2022, sec. rich list 2022. https://www.thetimes.co.uk/article/giving-list-philanthropy-uk-sunday-times-rich-list-37v38d2mq.

McDevitt, Jack, Jack Levin, and Susan Bennett. 2002. “Hate Crimes Offenders: An Expanded Typology.” Office of Justice Programs. 2002. https://www.ojp.gov/ncjrs/virtual-library/abstracts/hate-crimes-offenders-expanded-typology.

Pettigrew, Thomas, and Linda Tropp. 2006. “A Meta-Analytic Test of Intergroup Contact Theory.” Journal of Personality and Social Psychology 90 (June): 751–83. https://doi.org/10.1037/0022-3514.90.5.751.

Sandholtz, Nathan, Michael Planty, and Lynn Langton. 2013. “Hate Crime Victimization, 2003-2011.”

Schiappa, Edward, Peter B. Gregg, and Dean E. Hewes. 2005. “The Parasocial Contact Hypothesis.” Communication Monographs 72 (1): 92–115. https://doi.org/10.1080/0363775052000342544.

Silverman, Alex. 2020. “Demographic Data Shows Which Major Sports Fan Bases Are Most Likely to Support or Reject Social Justice Advocacy.” Morning Consult (blog). September 10, 2020. https://morningconsult.com/2020/09/10/sports-fan-base-demographic-data/.

Stening, Tanner. 2021. “Why Hate Crimes Are Underreported–and What Police Departments Have to Do with It.” News @ Northeastern. August 23, 2021. https://news.northeastern.edu/2021/08/23/why-hate-crimes-are-underreported-and-what-police-departments-have-to-do-with-it/.

Stephens-Davidowitz, Seth. 2014. “The Cost of Racial Animus on a Black Candidate: Evidence Using Google Search Data.” Journal of Public Economics 118 (October): 26–40. https://doi.org/10.1016/j.jpubeco.2014.04.010.

Stephens-Davidowitz, Seth, and Steven Pinker. 2017. Everybody Lies: Big Data, New Data, and What the Internet Can Tell Us about Who We Really Are. First HarperLuxe edition. New York, NY: HarperLuxe, an imprint of HarperCollins Publishers.

Wagner, Ben. 2021. “‘Beyond Our Wildest Dreams’: Milwaukee’s Deer District Rises to National Prominence.” WISN. June 29, 2021. https://www.wisn.com/article/beyond-our-wildest-dreams-milwaukees-deer-district-rises-to-national-prominence/36869480.