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Can Exposure to Celebrities Reduce Prejudice?*

The Effect of Mohamed Salah on Islamophobic Behaviors and Attitudes

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Abstract

Can exposure to successful celebrities from stigmatized groups reduce prejudice toward that group at large? We exploit the sudden and phenomenal rise to fame of Liverpool F.C. soccer star Mohamed Salah, a visibly Muslim player, to answer this question. We causally estimate the effect of Salah joining Liverpool F.C. on Islamophobic attitudes and behaviors using 936 county-month hate crime observations, 15 million tweets from U.K. soccer fans, and an original survey experiment of 8,060 Liverpool F.C. fans. We find that Merseyside county (home to Liverpool F.C.) experienced a 18.9% drop in hate crimes relative to a synthetic control, while no similar effect was found for other types of crime. We also find that Liverpool F.C. fans halved their rates of posting anti-Muslim tweets (a drop from 7.2% to 3.4% of tweets about Muslims) relative to fans of other top-flight English soccer clubs. The survey experiment suggests that these results may be driven by increased familiarity with Islam. Our findings indicate that positive exposure to outgroup role models can reveal new information that humanizes the outgroup writ large.

Keywords: prejudice, migration, intergroup contact, hate crimes

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> ... [Salah is] Muslim, and live[s] that in a world where these things are very often discussed in a dangerous manner, where people think 'they are all like this' or 'they are all like that'... it's nice to have somebody around full of joy, full of love and to do what he is doing around his religion. …[H]e is very influential for us. And if somebody thinks he is influential for the rest of the world as well then good, show it. …[I]t's an important statement for the world.
>
> – Jürgen Klopp, Liverpool F.C. Manager, on Mohamed Salah being named one of the TIME 100 Most Influential People on April 19, 2019.

In February 2018, fans of one of England's most dominant soccer clubs, Liverpool F.C., celebrated a decisive victory in Europe's most elite league. A 5 - 0 defeat of F.C. Porto in the UEFA Champion's League previewed an excellent season that saw Liverpool advance to the final. Mohamed Salah, a young Egyptian winger, was key to the club's success. After the victory, fans chanted:

If he scores another few
Then I'll be Muslim, too
If he's good enough for you
He's good enough for me
Sitting in a mosque...
That's where I wanna be.

Fans created more homespun chants as Liverpool F.C. continued their successful season:

Mohamed Salah
A gift from Allah...
He's always scoring
It's almost boring
So please don't take
Mohammed away.

The centrality of Salah's Muslim identity to these chants fueled media speculation that his success might be reducing Islamophobia among fans (The National, 2018; Thomas, 2018). European fans were not accustomed to seeing players prostrate in Muslim prayer (*sujood*) after scoring goals. So emblematic is Salah's *sujood* that the celebration is included in the video game FIFA 2019, played by millions worldwide. Salah's conspicuous Islamic practice at the most elite level of global soccer is arguably unprecedented. Some pundits argued that Salah portrayed "favorable images of Muslims, helping to reduce stereotypes and break down barriers within communities" (Monks, 2018). Others disagreed. Despite the fact that "everyone loves a winner," there was still no systematic evidence that Salah's fame could "in any way decrease the mainstream Islamophobia in British culture" (Al-Sayyad, 2018). Muslims remain one of Britain's most discriminated against groups, and the vast majority are of South Asian rather than Arab descent like Salah (Stevenson et al., 2017; Sedhi, 2004). But beyond anecdotal evidence, little is known about whether Salah has had a systematic impact on Islamophobia.

Motivated by the literature on social contact, we test the proposition that Salah's meteoric rise has reduced Islamophobia among Liverpool F.C. fans using three complementary research designs: an analysis of hate crimes in England, an analysis of anti-Muslim tweets among soccer fans, and an original survey experiment. First, we draw on hate crime data from 25 police departments in England between 2015 and 2018. We employ a variant of the synthetic control method[1] to generate a counterfactual hate crime rate for Merseyside county — where Liverpool F.C. is located — after Salah was signed. We find that Merseyside experienced a 18.9% lower hate crime rate after Salah was signed relative to the expected rate had he not been signed. The observed decrease is larger in Merseyside than in all placebo counties, suggesting the result is not merely due to chance. Moreover, the decrease in hate crimes in Merseyside is not attributable to a general decline in crime: there is a larger relative decline in hate crimes than any other crime category.

Second, we analyze 15 million tweets produced by followers of prominent soccer clubs in the English Premier League. We identify tweets about Muslims using keywords and train a classifier to label these tweets according to whether or not they express anti-Muslim sentiment. Using the same synthetic control method as in our hate crime analysis, we generate a counterfactual anti-Muslim tweet rate by fans of other teams. We find that the proportion of anti-Muslim tweets produced by Liverpool F.C. fans after Salah joined was 53.2% lower than the expected rate had he not joined Liverpool (3.4% versus 7.2% of tweets related to Muslims).

Finally, we implement a survey experiment among 8,060 Liverpool F.C. fans to test possible mechanisms of prejudice reduction that might explain these declines in prejudicial behavior. The results suggest that exposure to Salah may reduce prejudice by familiarizing fans with Islam. Priming respon-

[1]For a detailed description of the synthetic control method see Section 3.

dents with information about Salah's religious practices boosted the belief that Islam is compatible with British values by around 5 percentage points, compared to the baseline rate of 18% among the control group. Treatments stressing Salah's success and agreeable character, on the other hand, did not shift attitudes — perhaps because this information was not novel to fans. These findings suggest that positive exposure to outgroup celebrities can reveal new and humanizing information about the group at large, reducing prejudiced attitudes and behaviors.

This "Salah effect" is likely not unique to Salah. Celebrities with role model-like qualities have long been thought to shape social attitudes. Jackie Robinson's self-control in the face of discrimination from teammates, opponents, and fans arguably made Americans "more color friendly," though not color blind, when he broke baseball's color barrier in 1947 (Schwartz, 1999). British-Bangladeshi Nadiyah Hussain, the headscarf-clad winner of the most watched program on British television, *The Great British Bake-Off*, was credited with doing "more for British-Muslim relations than 10 years of government policy" after her 2015 win (Wiseman, 2018; Aly, 2015). The 2018 reboot of *Queer Eye for the Straight Guy* has similarly been lauded as a "tool for helping people unlearn" prejudice (Reyes Jr., 2018). Descriptive representation scholars theorize that the presence of minorities in positions of power or high visibility can translate into more favorable policies toward that group (Pitkin, 1967). Here we investigate how exposure to such minority figures can breed familiarity and tolerance among society at large. Such an effect has been alluded to anecdotally across time and space: we attempt to test it empirically in the case of Mohamed Salah.

The rest of the paper is structured as follows. In Section 1, we draw on the social contact literature to generate empirical hypotheses. Section 2 provides context on Islamophobia in the U.K. Section 3 presents our analysis of English hate crime data. In Section 4, we analyze tweets produced by Twitter followers of English Premier League clubs. Section 5 describes our original survey experiment exploring the mechanisms through which we might observe a Salah effect. Finally, in Sections 6 and 7, we interpret the results and speak to their generalizability.

1 Exposure and Prejudice

How might exposure to Salah affect attitudes or behaviors toward Muslims more broadly? Viewing exposure as a one-sided form of social contact, we can draw expectations from the rich literature on the contact hypothesis and exposure to outgroups. The contact hypothesis proposes that contact across social lines can reduce prejudice if that contact is positive, endorsed by communal authorities, egalitarian, and involves cooperating to achieve a common goal (Allport, 1979). Contact meeting these conditions has been shown to improve intergroup relations in diverse contexts including between roommates in South Africa (Burns, Corno and La Ferrara, 2015) and in the U.S. (Carrell, Hoekstra and West, 2015), and between classmates (Rao, 2019), teammates (Lowe, 2017), and neighbors (Barnhardt, 2009) in India. Positive intergroup contact is also associated with reduced racial anxiety in general (Pettigrew, 1998) and among white Britons interacting with Muslims in particular (Hutchison and Rosenthal, 2011). These results are affirmed by meta-analyses concluding that, with notable exceptions (Scacco and Warren, 2018), positive social contact "typically reduces prejudice" (Pettigrew and Tropp, 2006; Paluck, Green and Green, 2018).

For Liverpool F.C. fans, exposure to Salah fulfills many of the criteria thought to translate intergroup contact into tolerance: fans share a common goal with Salah, trusted authority figures (e.g. club management and staff) endorse Salah's presence on the squad, and the experience has been largely positive throughout the study period (Pettigrew and Tropp, 2006). Yet exposure to a celebrity like Salah is neither cooperative nor egalitarian. As Paluck, Green and Green's 2018 meta-analysis shows, we know little about the relative importance of these conditions in driving tolerance, making it difficult to assess whether exposure to Salah would reduce prejudice.

Interventions that manipulate exposure to outgroups rather than direct social contact may be more applicable to our study of possible Salah effects. Contact typically involves a two-sided interaction, while exposure is one-sided and lacks interaction (Table 1). Findings from exposure interventions are mixed. Exposure worsened prejudice toward ethnic (Enos, 2014) and economic (Sands, 2017) minorities in the U.S., and toward refugees in Greece (Hangartner et al., 2019). In contrast, another study finds that exposure to refugees in Austria reduced support for a far-right political party, possibly because natives in exposed municipalities interact frequently with newcomers (Steinmayr, 2016). Overall, this research suggests that being exposed to members of an outgroup without meaningfully interacting with them may trigger backlash effects. The outgroup members in these interventions, however, differ from Salah in at least three important ways: they are strangers, they appear in groups, and they do not carry a positive valence, as Salah does for Liverpool F.C. fans. Expectations generated from the research on exposure are thus inconclusive, and if anything, lean toward negative effects on tolerance.

A related literature also manipulates exposure, but to imagined outgroup members rather than real ones. This class of interventions embeds exposure via narratives, online games, or perspective-taking exercises that encourage subjects to view life through the perspective of outgroup members, or to imagine positive interactions with outgroup members. This type of exposure has generally been found to increase empathy across a variety of country contexts and outgroups (Lemmer and Wagner, 2015; Todd and Galinsky, 2014; Simonivitz, Kezdi and Kardos, 2018; Adida, Lo and Platas, 2018; Broockman and Kalla, 2016). Exposure to Salah is experientially very different from imagining a hypothetical outgroup member, however, thereby limiting our ability to generalize from these studies. As cautioned by Paluck, Green and Green (2018), naturalistic studies are likely to involve some portion of negative contact experiences, which can aggravate prejudice. Nevertheless, the success of empathy-building interventions implies that humanizing information about the outgroup, delivered in a personalized way, can reduce prejudice. Table 1 summarizes the predicted effects of these different types of interactions.

Table 1: Predicted Effects of Contact on Prejudice

		Interaction	
		Contact	*Exposure*
Outgroup	*Real*	Positive (e.g. roommates, teammates)	Negative (e.g. share a subway car)
	Fictional	N/A	Positive (e.g. online role-playing game)

Note that ‘contact’ here refers to cooperative rather than competitive contact, which can worsen intergroup attitudes.

On the one hand, exposure to Salah is well-suited to reveal information about Muslims in a similarly humanizing fashion. By watching games, post-game interviews, promotional videos released by the club, and content on Salah's social media pages, fans are exposed to rich information about Salah's life on and off the field. Viewers see what a Muslim prayer looks like, perhaps for the first time, when Salah scores. Salah can also be seen pointing his index finger to the sky while reciting the *shahada* (the Muslim profession of faith). Fans may learn about the rhythms of the holy month of Ramadan when Salah posts photos of himself breaking fast with an explanatory caption. Die-hard fans will also know that Salah's daughter, Makka, is named after Islam's most sacred site. His veiled wife can often be seen cheering him on from the sidelines at Anfield stadium. On the other hand, Salah's conspicuous religiosity may remind viewers of the ways in which Muslims differ from mainstream English soccer fans. If exposure to Salah instead highlights differences between mainstream fans and Muslims, then exposure may have a weak or negative effect on tolerance.

In summary, research on social contact produces contrary expectations when it comes to possible Salah effects. Interventions that yield positive effects tend to either involve two-sided, cooperative contact, or one-sided exposure to fictional or imagined outgroup members. It remains unclear whether we should expect exposure to Salah — one-sided exposure to a real-life outgroup member — to reduce prejudice toward Muslims at large.

2 Context: Islamophobia in the U.K

Islamophobia in the U.K. has been rising steadily since September 11th, 2001 (Elahi and Khan, 2017), in line with trends in attitudes toward Islam and immigration in other European countries (Heath and Lindsay, 2016). Figure 1 presents survey data from YouGov on the proportion of the British public agreeing with the notion that "there is a fundamental clash between Islam and the values of British society" from 2015 to 2018. Endorsements of this statement increased sharply between 2015 and 2017, when close to 60% of the British public responded that Islam clashes with British values. Despite a slight decrease in agreement since 2017, over half of respondents continued to affirm this anti-Muslim sentiment in 2018.

High levels of prejudice compound other disadvantages faced by British Muslims. Data from the

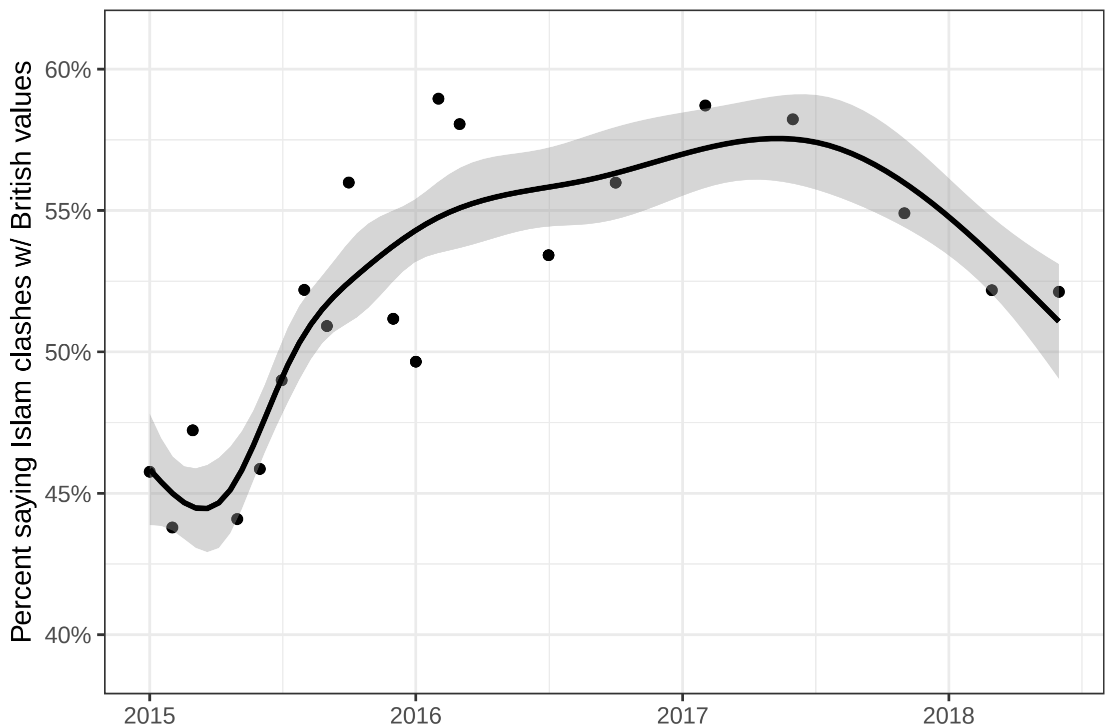


Figure 1: Attitudes toward Islam in the British public between 2015 and 2018. The vertical axis is the percentage of survey respondents stating that "there is a fundamental clash between Islam and the values of British society." Points are weighted averages within survey waves; the trend line is a spline fit to all 34,409 survey respondents using survey weights. Source: The YouGov-Cambridge Center.

2014 Office for National Statistics' Labour Force survey show that Muslim men are up to 76% less likely to be employed, and Muslim women up to six times less likely, than their white, non-Muslim counterparts (Khattab and Johnston, 2015). A government report concluding that "Muslims experience the greatest economic disadvantages of any group in U.K. society" attributed part of this disadvantage to discrimination in the workplace (Stevenson et al., 2017). Discrimination likely extends beyond the labor market. Over a quarter of British Pakistanis feel discriminated against on the housing market compared to 1% of white Brits according to a 2013 survey, and Muslims consistently report poorer health outcomes relative to other religious groups (Mcleod, 2013; Elahi and Khan, 2017). Prejudice against Muslims also seems to beget violence. While race or ethnicity already motivated 82% of hate crimes in England and Wales in 2012 (Office, 2012), reported abuse against Muslims increased by 92% between 2015 and 2017 according to one watch group (Tell Mama, 2017).

3 Analysis of Hate Crimes in the U.K.

We begin with arguably a hard test of any Salah effects: an analysis of hate crimes in the U.K. Hate crimes are rare events that are likely to be perpetrated by extreme bigots. Hate crimes are also public acts, and as such are likely to be subject to social pressure. A reduction in hate crimes requires either that the underlying beliefs of these bigots have changed, or that hate crimes are less socially acceptable. If Salah's signing decreased the general public's tolerance of hate crimes, or changed the underlying beliefs of bigots, then we would expect to see fewer hate crimes. We test this proposition via an event-study analysis that leverages hate crime statistics in Merseyside — the county that contains the city of Liverpool — and over two dozen other police jurisdictions in the U.K. We find that hate crimes in Merseyside were significantly lower after Salah joined Liverpool F.C. than we would have otherwise expected.

3.1 Data

To gather data on hate crimes, we submitted Freedom of Information requests (FOI) to every police department in England in April 2018. Police departments are roughly coterminous with counties. We requested a dataset consisting of every hate crime that was reported to the department between January 2015 and April 2018, along with information including the date, location, motivation for the crime, and demographic information about the victim. We include counties if their response provided sufficient information for us to calculate the total number of hate crimes reported in the jurisdiction each month, yielding usable data from 25 police jurisdictions out of the 39 contacted, and 936 month-county observations. Hate crimes themselves cover a range of offenses. Common violations include harassment, aggravated common assault, criminal damage to vehicles, and aggravated public fear, alarm, or distress. In order to be classified as a hate crime, police should have a clear indication that the perpetrator targeted the victim mainly on the basis of their religious, racial, sexual, or abilities-based identity.

Our main outcome variable is an annualized hate crime rate per thousand residents. For instance, a county with a population of 100,000 that experiences 10 hate crimes in a given month has an annual hate crime rate of (10 / 100,000) $\times$ 1,000 $\times$ 12 = 1.2 hate crimes per thousand residents in that month.[2] The dependent variable ranges from 0 to a maximum of 4.342, with a mean of 0.951 and standard deviation of 0.767. We consider Liverpool's home county of Merseyside to be treated after Salah's official signing in June 2017.[3] When Salah joined, his transfer fee constituted a club record, stoking interest in the player among the club's fans. While a Salah effect is likely to be most pronounced after his stellar performances with the team in late 2017, any other sharp cutoff would be arbitrary.[4] Figure 2a shows the panel structure of the data, along with the treatment status, and Figure 2b plots the raw time series data for each county, with Merseyside highlighted. In the pre-treatment period, hate crimes are relatively common in Merseyside. Averaging over all pre-treatment observations, the hate crime rate in Merseyside is higher than 19 of the other 24 counties in the data.

In our analysis, we use all reported hate crimes. We requested data on hate crimes broken down by victim religion and ethnicity, but the responses were inconsistent. In some cases, police departments do not collect this information; in others, they began collecting it near the end of the study period. As a result, we include all reported hate crimes. The focus on all hate crimes should still reflect trends driven by anti-Muslim incidents: the Home Office reports that 76% of hate crimes perpetrated from January 2017 to January 2018 were religiously or racially motivated.[5] Of these crimes, 52% were categorized as anti-Muslim in particular (BBC News, 2018*a*).

3.2 Research Design

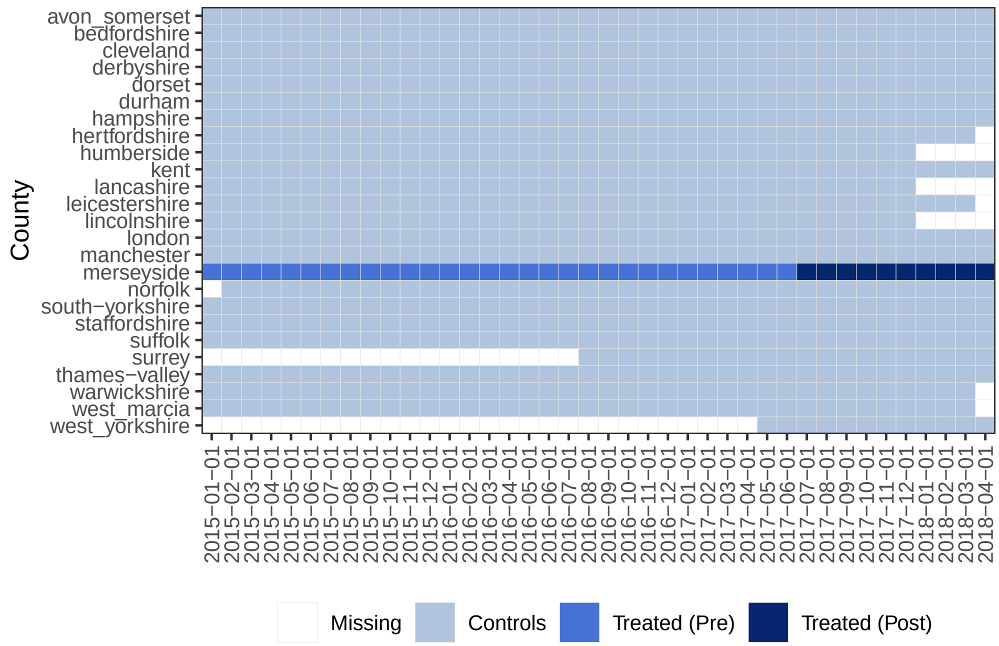
Our goal is to estimate how hate crimes in Merseyside changed after Salah joined Liverpool F.C., relative to what they would have been had he not joined the team. As seen in Figure 2b, there is a downward trend in hate crimes in Merseyside during the treatment period. However, simple before-after analyses of hate crimes in Merseyside might be misleading, since a number of factors that are not

[2]It is worth noting any other normalization procedure would yield identical results, up to a multiplicative constant.

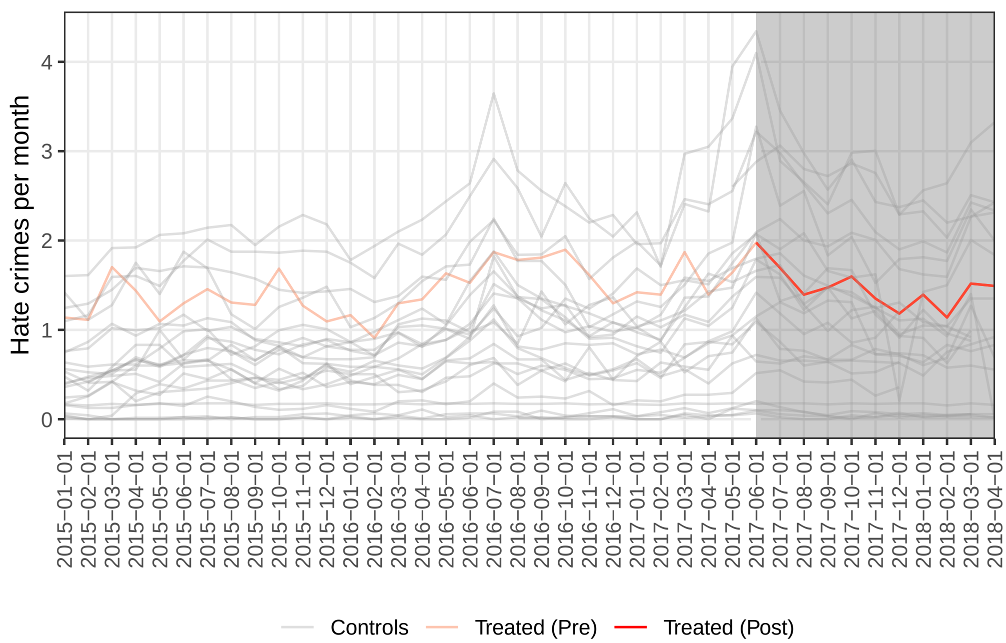
[3]Merseyside county encompasses both Everton F.C. and Liverpool F.C. fans. A potential backlash from Everton fans would dilute any treatment effects for the hate crime analysis, biasing against finding an effect.

[4]See Appendix A for evidence that interest in Salah — as measured by Google search trends — spiked shortly after he was signed in the summer of 2017 and then began to steadily increase afterwards through mid 2018. We discuss other events relevant to Islamophobia that occurred around this time in Section 6.

[5]Note that the same offense can be categorized as both racially and religiously motivated.



(a) Data structure



(b) Outcome data

Figure 2: Visualization of hate crime data. Panel (a) shows the panel-data structure and panel (b) plots the outcome variable in each police jurisdiction.

specific to Merseyside may be driving down hate crimes across the country.

Instead, we propose using the pre-treatment data from Merseyside and the control group data — hate crime statistics from counties other than Merseyside — to construct a plausible counterfactual for Merseyside in the post-treatment period. A number of methods have been developed for inference in settings like ours, including two-way fixed effects models, interactive fixed effects, the synthetic control method, and matrix completion methods (Abadie, Diamond and Hainmueller, 2010; Doudchenko and Imbens, 2016; Xu, 2017; Athey et al., 2018). Roughly speaking, these methods attempt to impute the unobserved outcomes in the post-treatment period by first looking for structure in the pre-treatment data that generates good predictions of the treated unit's outcomes in the pre-treatment period. The same structure is then applied to the post-treatment period to generate estimates of the counterfactual potential outcome for the treated unit. To obtain an estimate of the treatment effect on the treated unit, we simply take the difference between the observed outcome for the treated unit in the post-treatment period and the imputed counterfactual outcome. Therefore, if there are T post-treatment periods, we obtain T treatment effect estimates. In addition, we compute the treatment effect averaged over the T post-treatment periods as a simple summary of the treatment effect.

Our main analysis uses the matrix completion method of Athey et al. (2018), as implemented in the `R` package `gsynth` (Xu, 2017). We selected this method because it outperformed other methods in approximating the outcome in Merseyside prior to the treatment period. As such, this method arguably generates a more suitable counterfactual estimate than others. This method attempts to find a low-dimensional matrix structure in the data by minimizing the mean squared error between the observed outcomes and the outcomes predicted by another (low-rank) matrix. To avoid overfitting, the procedure penalizes the complexity of the matrix by adding a penalty term proportional to the nuclear norm of the matrix, with the scaling factor chosen via leave-one-out cross-validation.[6]

[6] In each cross-validation iteration, we omit one pre-treatment observation for the treated unit. We then select the penalization parameter that produces the smallest mean-squared prediction error for the held out observations.

3.3 Inference

Inference in the setting of a single treated unit is challenging. Standard methods to computing standard errors based on asymptotic theory obviously do not apply. We implemenet several complementary approaches to inference: the nonparametric bootstrap, a permutation-based method of generating a null distribution, and using other types of crime as placebo outcomes.

First, uncertainty estimates can be generated for the matrix completion method using the nonparametric bootstrap. By repeatedly resampling control units and re-estimating the model on the bootstrap samples, we generate a distribution of the treatment effect estimator. We can then compute a standard error by taking the standard deviation of bootstrap estimates and obtain confidence intervals by taking the appropriate quantiles of the bootstrap distribution.

Second, we reshuffle units' treatment status to generate a null distribution. For each control unit, we pretend it was in fact treated and estimate the "treatment effect" on the placebo treated unit. By construction, there is 0 treatment effect for these units (since they were not actually treated), so this procedure generates a distribution of the treatment effect estimator under the sharp null of no treatment effect in any period, for any unit. We can then take the actual Merseyside estimates and compare them to the null distribution to generate a permutation-based p-value. This method of inference is proposed by Abadie, Diamond and Hainmueller (2010).[7]

Finally, we use other types of crime as placebo outcomes that are unlikely to be affected by changes in anti-Muslim sentiment. We collected data from the U.K. Home Office on crime at the police jurisdiction level.[8] While these data do not track hate crimes, they are formatted in a standard set of 14 crime types, such as shoplifting, robbery, possession of weapons, drugs, and so on. There is little reason to believe that these crimes would be affected by a decrease in anti-Muslim sentiment. If we find a significant decrease in these crimes in Merseyside after Salah was signed, it would indicate that any decrease in hate crimes is part of a more general trend, not an effect of Salah's signing.

[7] In implementing this method, we omit West Yorkshire because we only have data for two pre-treatment months, as seen in Figure 2a. In all, there are 23 placebo units we use for this procedure.

[8] Data were downloaded from the U.K. police data download page (`https://data.police.uk/data/`). Accessed on May 22, 2019.

To conduct this placebo-outcome analysis, we restrict the data to the same set of county-month observations used in the hate crime analysis. We use the same matrix completion procedure to generate treatment effect estimates for each crime type. Since the prevalence of different types of crime varies substantially (for example, shoplifting is very common and hate crimes are very uncommon), we generate comparable estimates by expressing the treatment effect estimates in terms of the pre-treatment average. We then compare the relative change in hate crimes to the relative change in other types of crime.

As a final robustness check, Appendix C presents an alternative method of estimating the treatment effect: a generalized difference-in-differences regression with time and unit fixed effects. In this framework, the ATT is identified given parallel trends of the potential outcomes for the treated and untreated units in the absence of treatment. To perform inference in this setting, we implement another permutation-based procedure. The results are substantively very similar to those presented in the main text using the matrix completion method.

3.4 Results

The main results are presented in Figure 3. The top plot shows the actual outcome data for Merseyside (solid line), along with the imputed counterfactual for Merseyside (dashed line). The bottom plot shows the difference between the observed and imputed outcomes in all periods for Merseyside (red) and all other placebo units (gray). In both plots, the shaded region indicates the post-treatment period. In the post-treatment period, the difference between the observed and imputed outcomes is the treatment effect estimate.

If the matrix completion method is performing well, the imputed estimates should closely match the observed outcomes in the pre-treatment period. Reassuringly, this is the pattern we see. In the top panel, the two lines in the pre-treatment period track each other closely. In the bottom plot, the pre-treatment line is close to 0 in most periods. While it fluctuates at times, there does not appear to be a trending pattern in the pre-treatment period that would cause concern about the validity of the treatment effect estimates.

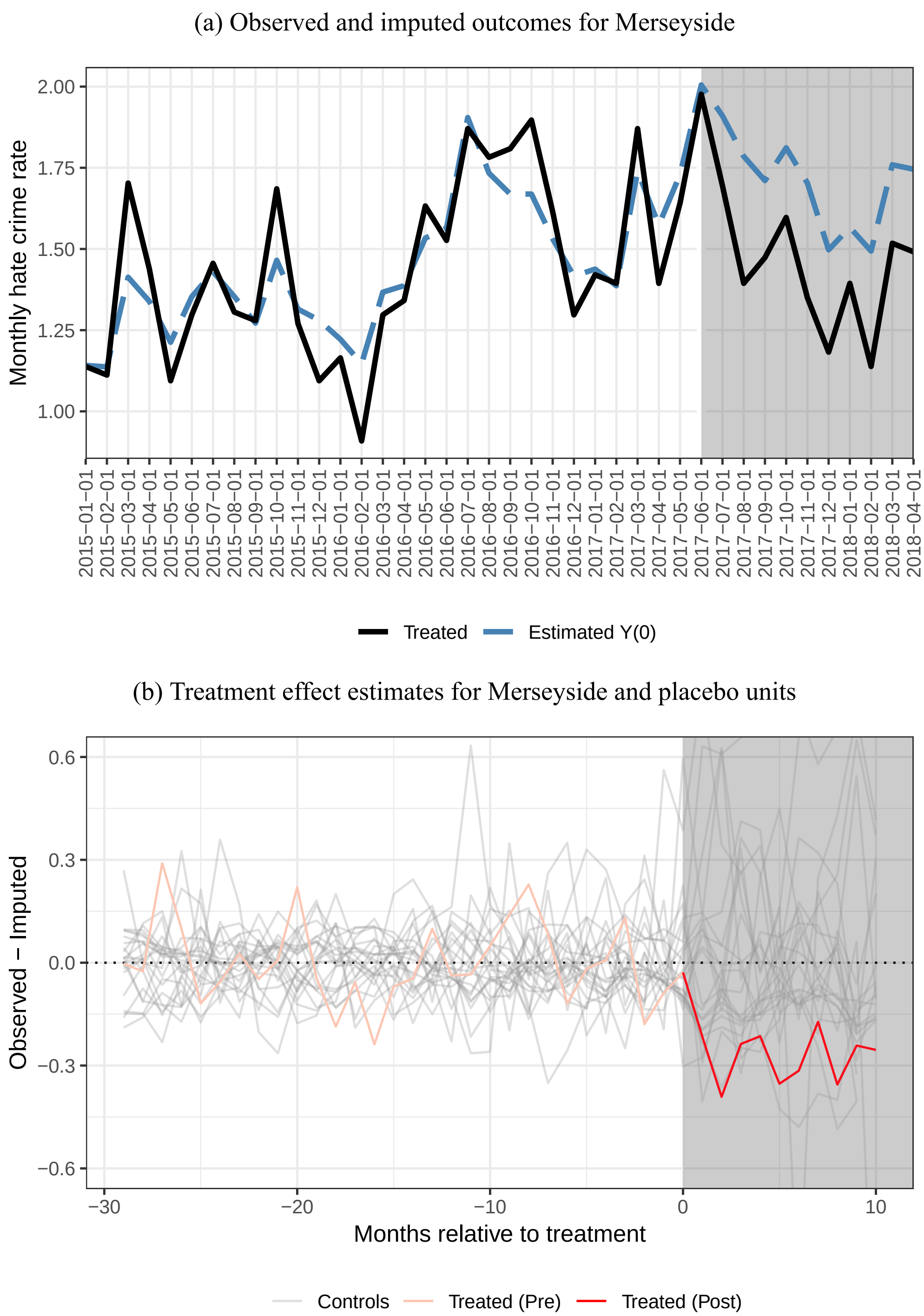


Figure 3: Matrix completion results. The top panel shows the observed (solid line) and imputed (dashed line) monthly hate crime rates in Merseyside. The bottom panel shows the difference between the observed and imputed outcomes. In the post-treatment period, this is the estimate of the treatment effect. The red line shows the estimates obtained for Merseyside, while the gray lines show the estimates obtained when we treat each of the control-group units as it were treated. The fact that the Merseyside estimates are consistently lower than the control-group estimates provides evidence that our treatment effect estimates are unlikely to be due to chance.

Moving on to the post-treatment periods, the observed levels of hate crime in Merseyside are consistently lower than what we would predict had there been no Salah effect. Averaging across all months in the post-treatment period, the difference between the observed outcome and imputed outcome is -0.275 annualized hate crimes per 1,000 residents. Compared to the pre-treatment average in Merseyside, this treatment effect represents an 18.9% drop in hate crimes. The bootstrap-based standard error for the treatment effect, averaging over post-treatment periods, is 0.067 and the central 95% confidence interval is $[-0.394, -0.155]$. Looking at the estimates month-by-month, the differences between the observed and imputed outcomes begin soon after Salah agreed to join Liverpool, in June 2017, and persist through at least April 2018 — the last month for which we have data.

The bottom plot in Figure 3 shows that the treatment effect estimate for Merseyside tends to be lower than placebo treatment effect estimates for other units. In some post-treatment months, there are placebo units with larger treatment effect estimates, but no placebo units estimates are as consistently negative as Merseyside. When we average across post-treatment periods, Merseyside has the lowest treatment effect estimate, and only two placebo units have treatment effect estimates that are larger in absolute value. Since there are 24 possible permutations of the treatment assignment — Merseyside plus 23 placebo units — the one-sided p-value is $1/24 = 0.042$ and the two-sided p-value is $3/24 = 0.125$.

This result suggests that the decrease in hate crimes observed in Merseyside is unusual relative to changes observed in other police jurisdictions. The change in hate crimes is consistent with a Salah effect, but it is unclear whether Salah was the cause of the decline. Instead, it could also be that there was a general decline in crime in Merseyside that happened to coincide with Salah's arrival at Liverpool F.C. If this were the case, we might observe a decrease in hate crimes relative to other police jurisdictions, even if Salah's arrival at Liverpool had no direct effect on hate crimes.

The placebo outcome analysis helps to address this concern. Figure 4 shows the treatment effect estimates for Merseyside for each of 15 different types of crimes — hate crimes, plus the 14 types tracked in the U.K. Home Office police data. The results show that the decrease in hate crimes is larger than changes observed for most other types of crime in Merseyside. Recall that the treatment effect for hate crimes was a 18.9% decrease, relative to the pre-treatment baseline. No other crime category saw such a large relative decrease, and only two, "drugs" and "public order," had changes that were larger in magnitude — and both of these were *increases* in crime (19.5% and 22.6%, respectively). Thus, the drop in hate crimes after Salah was signed does not appear to be attributable to a general decrease in crimes in Merseyside.

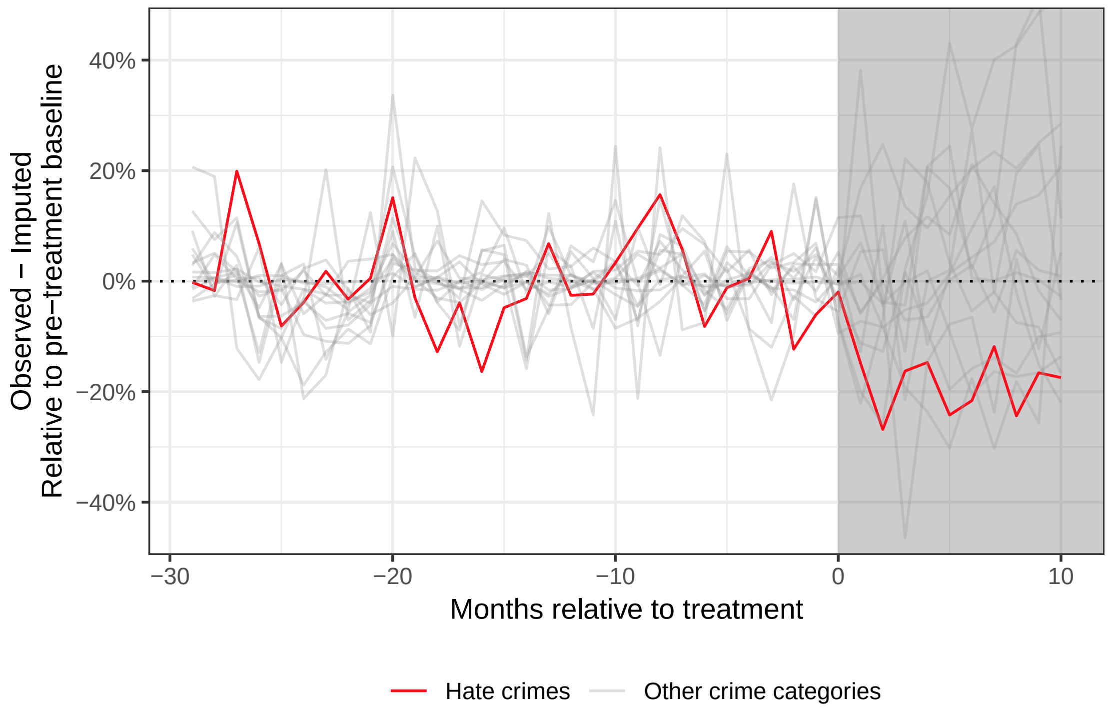


Figure 4: Matrix completion results for all crime types in Merseyside. The red line shows the treatment effect estimate for hate crimes and the gray lines show treatment effect estimates for each of 14 types of crimes defined by the U.K. Home Office. To generate estimates on comparable scales across crime types, the treatment effect estimates are expressed as a percent of the pre-treatment mean for each crime type. The estimated treatment effect on hate crimes is consistently more negative than the estimate for any other crime outcome.

Overall, we interpret these results to support the hypothesis that Salah's arrival at Liverpool F.C. caused a decrease in extreme acts of bigotry. Hate crimes in Merseyside were lower after Salah was signed than we would expect given prior hate crime trends and the trends of other police jurisdictions after Salah was signed. This decline was more extreme than we would expect based on chance alone, and the decrease in hate crimes was more pronounced than the decrease in any other crime category.

Taken together, the evidence points to Salah's rise in prominence causing a decrease in hate crimes in Liverpool F.C.'s home county.

4 Analysis of U.K. Soccer Fans' Tweets

Our analysis of hate crimes in the U.K. provides evidence that Salah joining Liverpool F.C. may have decreased hate crimes in Merseyside relative to their expected rates if he had not joined Liverpool F.C. Although hate crimes are extremely harmful and consequential, they are quite rare and severe events. As such, they tell us little about how Salah's signing may have impacted more quotidian forms of Islamophobia among mainstream Liverpool F.C. fans. To gain more purchase on this question, we analyze approximately 15 million tweets produced by U.K.-based soccer fans in the period preceding and following Salah joining Liverpool F.C.

4.1 Data

As of 2018, about one quarter of the U.K.'s population was an active Twitter user. While this constitutes a large subsection of the U.K. population, recent research indicates that U.K. Twitter users are not representative of the U.K. population as a whole. They are disproportionately young, male, and more likely to have managerial, administrative, and professional occupations (Sloan, 2017). However, the platform is widely used by British soccer fans, with 3 of the top 20 most followed accounts in the U.K. belonging to English Premier League teams, alongside popular news accounts like the BBC and celebrities such as Harry Styles and Emma Watson (Social Backers, 2019). Twitter data thus gives us access to public messages produced by a large cross-section of U.K. soccer fans.

Looking at soccer fans based in the U.K., we compare the frequency of anti-Muslim tweets published by fans of Liverpool F.C. relative to fans of other English teams over time. We began by using Twitter's API to scrape the account IDs of all followers of the top five most followed teams in the English Premier League: Manchester United (19 million followers), Arsenal (14 million), Chelsea (12 million), Liverpool (11 million), and Manchester City (6 million). We also scraped the followers of

Everton, a smaller team with 1.75 million followers that is also located in the city of Liverpool. Fans of both clubs are nearly identical in terms of demographics: the home stadiums are within walking distance of each other, there are no historic political, religious, or social differences between their fanbases, and many Liverpudlian families are mixed in their allegiances (Borden, 2014). Evertonians thus constitute the closest comparison group in the sample, with one key difference as a result of their fierce rivalry: exposure to Salah may skew negative for Evertonians, but is positive and goal-aligned for Liverpool F.C. fans.

After obtaining followers' account IDs, we collected our sample of tweets as follows. First, to ensure that the users in our sample had been soccer fans prior to Salah joining Liverpool, we subset our follower IDs to the oldest 500,000 followers of each team. Follower IDs are scraped from Twitter's API in the reverse order that the users began following the account, with newer users appearing first. This feature of the data enables us to identify long-term fans of each team, given that the team accounts have been popular for almost a decade and now have millions of followers. Then, to ensure that users in our sample were located in the U.K., we again used Twitter's API to download profile metadata for the 500,000 oldest followers of each team.[9] We then used their "user.location" metadata field to determine if each user was located in the U.K. based on the text of their self-reported locations.[10] Once we identified longtime Twitter followers of English Premier League teams that were likely to be located in the U.K., we randomly sampled 10,000 followers from each team. We used Twitter's API a final time to scrape up to 3,200 of the most recent tweets published by each of these 60,000 U.K. soccer fans.[11] This resulted in a dataset of approximately 15 million tweets produced by the 60,000 English

[9]This method ensures that the sample joined Twitter before the treatment. For instance, the 500,000 most recent followers for Liverpool F.C., and the most recent accounts, were created between 2015 and mid-2016.

[10]Users were classified as being located in the U.K. if their "user.location" metadata field contained either a city or country keyword indicating that the user was located in the U.K. City keywords were obtained using the `maps` package in `R`. While this method does not necessarily capture all fans of these soccer teams located in the U.K., as many users do not provide any location metadata at all, it ensures that our sample consists only of likely U.K. residents. As Hecht et al. (2011) demonstrate, a user's country and state can be determined with decent accuracy using self-reported Twitter data, and users often reveal location information with or without realizing it. Similarly, Mislove et al. (2011) explain that because large numbers of users report their location in the "user.location" field and in aggregate these reports are quite accurate, this is a reasonable way to determine a user's location. This is particularly true given that we are more interested in obtaining a high degree of precision (ensuring that the users are actually U.K. residents) than recall (obtaining the entire population of tweets sent by U.K. residents).

[11]The 3,200 tweet limit is imposed by Twitter's API and for most Twitter users covers their entire Twitter timelines beginning on the day they first joined the platform.

followers of the "Big Five" clubs of English soccer plus Everton F.C.

In order to identify anti-Muslim tweets, which are relatively rare in this dataset of all tweets produced by soccer fans in the U.K. (approximately .03% of all tweets), we first identified all tweets broadly about Muslims in our dataset. We began with the terms "muslim" and "islam" and used a word2vec model (a neural network that processes text) to find other relevant terms in the data. This yielded the following broad relevant keywords: "arab," "arabs," "islam," "muslims," "muslim," "mosque," and "mosques."[12] About 44,000 of the 15 million tweets in our dataset contained one of these relevant keywords. We then took a sample of about 1,500 of these tweets containing a keyword relevant to Muslims or Islam and used Figure8 (formerly Crowdflower), a crowd-sourced data enrichment platform, to have three native English speakers code each of these 1,500 tweets as anti-Muslim or not.[13]

Using this human-coded data, we trained a Naive Bayes classifier to classify all of our tweets containing one of the keywords described above as anti-Muslim or not. Our classifier's out of sample performance yielded scores of 88% Accuracy, 98% Precision, 90% Recall, and an F1 score (harmonic mean of Precision and Accuracy) of 94%. However, because anti-Muslim tweets were relatively rare in our data, and our training dataset was not balanced, Balanced Accuracy (i.e. the average of the proportion of tweets classified correctly in each class individually) is a better and more conservative measure of classifier performance. Our classifier performed with 70% Balanced Accuracy. Given that intercoder agreement among human coders was 76%, we are satisfied that our classifier gives us a reasonable, if imperfect, measure of anti-Muslim sentiment in our tweets. We then used this classifier to classify all 44,000 tweets relevant to Islam or Muslims in our dataset as anti-Muslim or not.[14] These classified tweets allowed us to develop monthly measures of the proportion of fans' anti-Muslim tweets

[12]The word2vec model also identified many irrelevant keywords to our study such as "rohingya" (in reference to the ongoing conflict in Myanmar) and "assad" (in reference to the Syria conflict). We only chose to include relevant keywords that were among the top 50 words that the word2vec model indicated were most similar to the terms "muslim" and "islam." Although most British Muslims are of South Asian descent, the word "pakistani" did not appear in the top 50 words identified by the word2vec model and therefore we did not use it as keyword to filter our data.

[13]The instructions provided to coders are displayed in Appendix D. For more information on using Figure8 (formerly Crowdflower) to code data for training classifiers, see Benoit et al. (2016).

[14]Tweets that did not contain relevant keywords were classified as irrelevant.

in their tweets about Muslims or Islam (relevant tweets).[15] Figure 5a shows the panel structure of the data, along with the treatment status, and Figure 5b plots the raw time series data for each team, with Liverpool F.C. highlighted.

4.2 Research Design

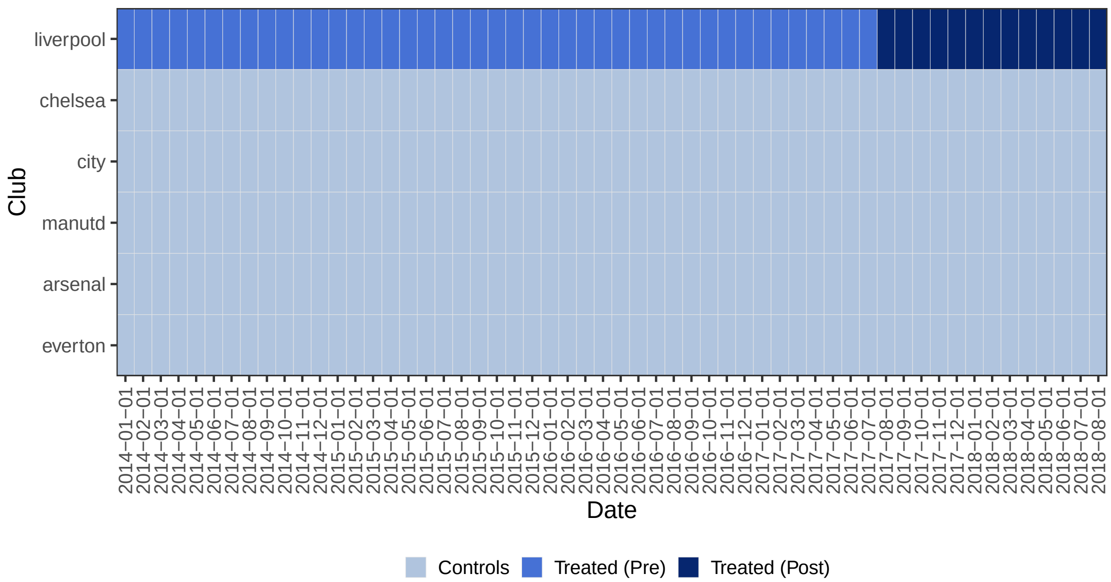
Following the approach we use to analyze hate crime data, our main analysis of the Twitter data again uses the matrix completion method of Athey et al. (2018), as implemented in the `R` package `gsynth` (Xu, 2017). This allows us to use the rates of anti-Muslim tweets published by fans of Liverpool F.C. and other clubs in the pre-treatment period to construct a plausible counterfactual for Liverpool F.C. fans in the post-treatment period. This, in turn, enables us to estimate how the rates of anti-Muslim tweets among Liverpool F.C. fans' tweets changed after Salah joined the club, relative to what they would have been if he had not joined.

4.3 Results

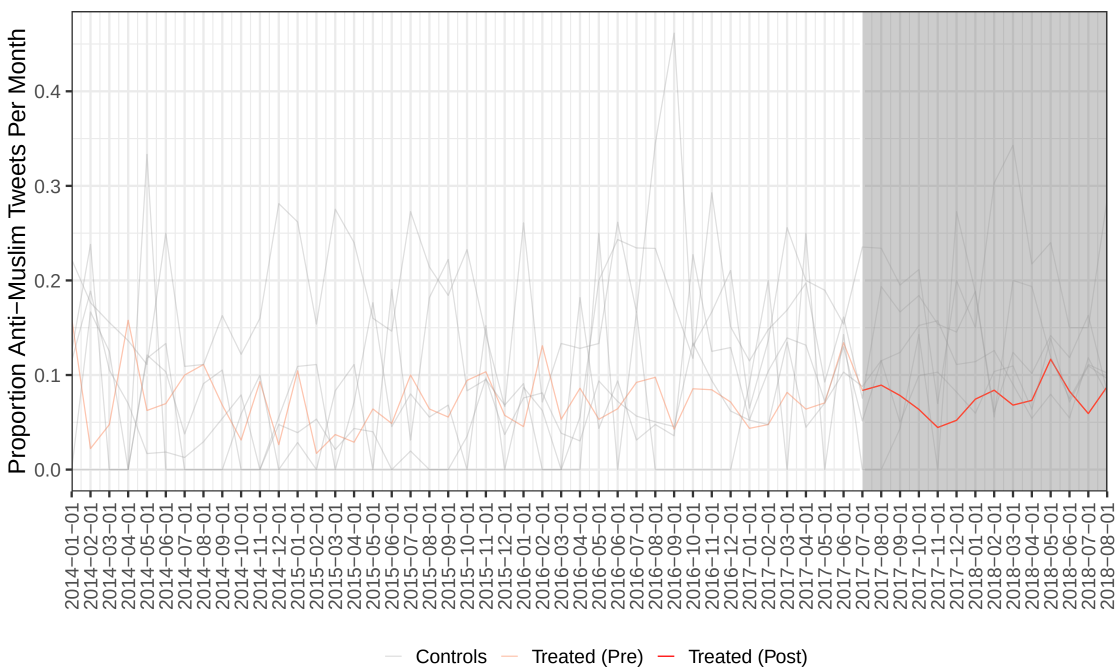
The main results are presented in Figure 6. The top plot shows the actual outcome data for Liverpool F.C. fans (solid line), along with the imputed counterfactual for these fans (dashed line). The bottom plot shows the difference between the observed and imputed outcomes in all periods for Liverpool F.C. fans (in red) as well as for fans of four other large football clubs (Arsenal, Chelsea, Manchester United, and Manchester City) and fans of Everton, the smaller club also located in Merseyside county described above. In both plots, the shaded region indicates the post-treatment period. In the post-treatment period, the difference between the observed and imputed outcomes is our estimate of the average treatment effect on the treated unit (ATT).

As in the hate crime results, if the matrix completion method is performing well, the imputed estimates should closely match the observed outcomes in the pre-treatment period. Again, we observe

[15] This measure is less sensitive to changes in the salience of topics related to Muslims or Islam than a related outcome: the proportion of anti-Muslim tweets in fans' total tweets. For example, terror attacks are often followed by an uptick in anti-Muslim language, but this is generally accompanied by much larger increases in tweets defending Muslims and Islam or condemning Islamophobia, as well as upticks in neutral tweets discussing the event (Magdy, Darwish and Abokhodair, 2015). We thus focus only on tweets relevant to Muslims or Islam to alleviate this concern.



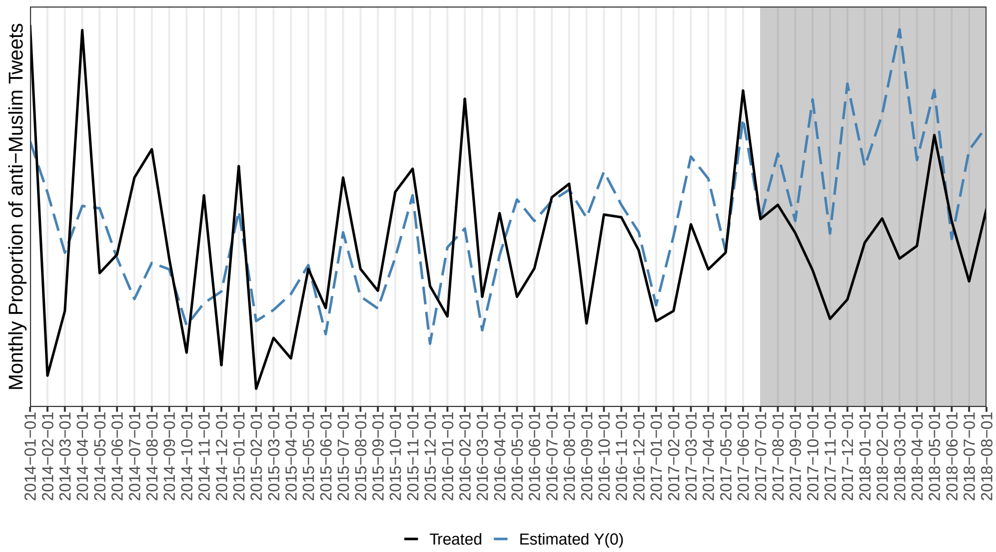
(a) Data structure



(b) Outcome data

Figure 5: Visualization of Twitter data. Panel (a) shows the panel-data structure and panel (b) plots the outcome variable for each soccer club.

(a) Observed and imputed outcomes for Liverpool



(b) Estimated ATT in every period (Liverpool vs. Other Clubs)

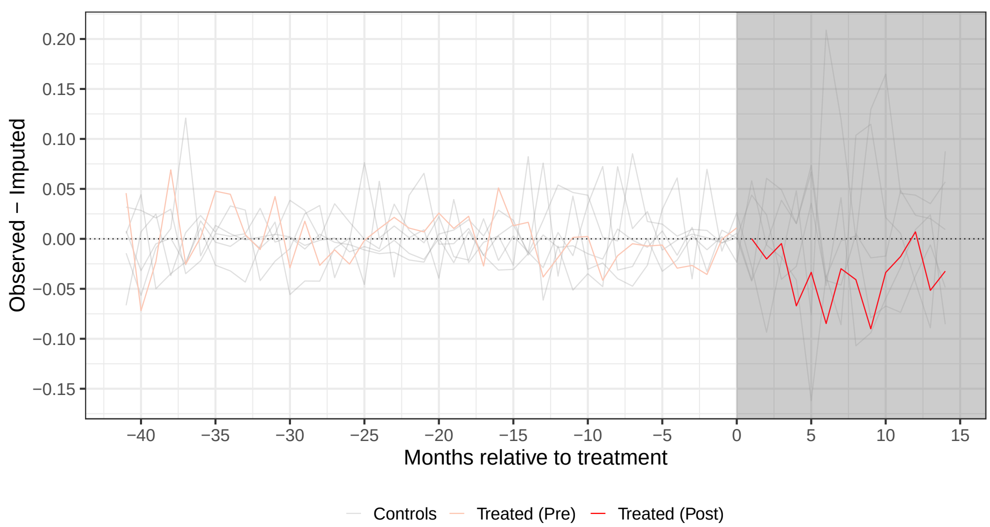


Figure 6: Matrix completion results. The top panel shows the observed (solid line) and imputed (dashed line) monthly proportion of anti-Muslim tweets in Liverpool fans' tweets that are relevant to Muslims or Islam. The bottom panel shows the difference between the observed and imputed outcomes. In the post-treatment period, this is the estimate of the ATT for Liverpool, compared to other prominent English clubs.

this pattern: the pre-treatment imputed and observed outcomes for Liverpool tend to be very similar, and there does not appear to be a pre-treatment trend that would threaten the validity of the treatment effect estimates.

Examining the post-treatment periods, the observed monthly proportions of anti-Muslim tweets among Liverpool fans are consistently lower than what we would predict had there been no Salah effect. Averaging across all months in the post-treatment period, the difference between the observed outcome and imputed outcome of the proportion of anti-Muslim tweets is -0.038 (bootstrap-based S.E. $= 0.007$). Compared to the pre-treatment average among Liverpool fans, this treatment effect represents a 52.3% drop in the proportion of anti-Muslim tweets in tweets about Muslims (from 0.072 to 0.034). Looking at the estimates month-by-month, the differences between the observed and imputed outcomes begin soon after Salah agreed to join Liverpool, in June 2017, and persist through at least May 2018 — almost a year after Salah joined the team.

When we employ the same permutation inference approach as in the hate crime section, only for Liverpool F.C. followers do we estimate a consistently negative treatment effect in the post-treatment period. The placebo estimates tend to oscillate between positive and negative treatment effects, while the Liverpool treatment effect estimates are negative in every post-treatment month but one — again suggesting that the observed estimate for Liverpool F.C. followers is unlikely to have occurred by chance. As a robustness check, we again present a generalized difference-in-differences approach in Appendix D. That analysis method generates very similar estimates as the ones reported here.

Overall, these results provide suggestive evidence that anti-Muslim tweets among Liverpool F.C. fans were lower starting in July 2017 than we would have expected based on their previous tweeting behavior, and that of other soccer teams. At the same time, this effect may be partly driven by the fact that fans of other teams may have become more prolific in their anti-Muslim rhetoric on Twitter following Salah's arrival. While we again cannot know with certainty that Salah is the sole (or even primary) cause of these results, our findings are again consistent with the Salah effect hypothesis.

5 Exploring Mechanisms via a Survey Experiment

The evidence presented above suggests that the arrival of Salah likely reduced anti-Muslim behavior among Liverpool F.C. fans. But how did this work? We propose three ways in which exposure to Salah might reduce Islamophobia. As outlined in the world's most popular online soccer publication, *Goal*: "Salah has won the hearts of the Anfield faithful through his affable nature, prolific goal-scoring ability and the way that he shows his love and respect for his religion openly" (Siregar, 2018). We directly test these mechanisms — personality, success on the field, and religiosity — using an original survey experiment among Liverpool F.C. supporters living in the U.K.

First, Salah's charismatic personality may help humanize Muslims. The cover article of TIME Magazine's 100 most influential people describes him as follows: "Mo Salah is a better human being than he is a football player. And he's one of the best football players in the world" (Oliver, 2019). Salah is often seen joking with his teammates with a signature grin, entertaining his young daughter on the sidelines, and respecting his opponents almost to a fault, for instance, by refusing to celebrate goals against his former clubs. Salah's portrayal as an agreeable friend, father, and teammate is counter-stereotypical, and as such may dampen the perception that Muslims are threatening while making Muslims seem less socially distant from white Brits (Rothbart and John, 1985). The "nice guy" mechanism aligns with the finding that likability can mediate exposure effects (Joyce and Harwood, 2014).

Second, there may be a "success" mechanism whereby Salah's soccer skills are driving down Islamophobia. In a relatively short period of time, Salah has enjoyed phenomenal success at the individual, club, and national levels (Oliver, 2019). In May 2018, he carried his club to the world's most watched annual sporting event: the UEFA Champion's League Final. One month later, Salah led the Egyptian national side to the FIFA World Cup for the first time in almost three decades. His remarkable breakout season earned him a nomination for the English Premier League's Player of the Year and the coveted FIFA Puskás Prize for Goal of the Year. Salah's success may therefore drive positive associations with Muslims writ large. If the success mechanism is at play, then positive attitudes toward the outgroup may be conditional on the success of their public figureheads, a claim made by several elite soccer stars of immigrant descent.[16]

Third, Salah familiarizes fans with the ways in which many Muslims practice their religion. Usually after scoring a goal, Salah prostrates in Muslim prayer. Salah's wife is often seen wearing hijab while his daughter is called Makka in honor of Islam's holiest site. Shedding light on Islamic practices might add nuance to viewers' perception of the religion, humanizing Islam from a monolith with potentially negative connotations to a complex, human, and individualized belief system. Social psychologists dub this the "mainstreaming" effect, whereby increased media exposure to outgroups may draw groups with disparate attitudes towards a more similar, tolerant viewpoint (Calzo and Ward, 2009). Several observational studies conclude that new, positive information about an outgroup, as revealed through intergroup exposure, can improve attitudes (Pettigrew, 1998; Weber and Crocker, 1983; Stephan and Stephan, 1984; Triandis, 1994). The information revealed by Salah about life for many Muslims is similarly new and positive for many fans, and revealed in a personalized manner consistent with best practices deployed in empathy-building interventions (Crisp and Turner, 2009; Batson et al., 2002).

5.1 Research Design

To test these mechanisms, we conduct a survey experiment of Liverpool F.C. fans in the U.K. The survey was conducted via Facebook advertisements to explore mechanisms through which Salah's rise may have reduced prejudice towards Muslims.[17] We targeted the survey to people who "like" the Liverpool F.C. page on Facebook and who live in the U.K.[18] These users saw a Facebook advertisement stating: "Help us research L.F.C.! Love Liverpool F.C.? Take 2 mins. to help us research Liverpool fans!" The survey was launched from October 2018 to January 2019, until $1,500 worth of clicks were

[16] When he left the German national team because of alleged racist abuse, Mesut Özil, who is of Turkish descent, stated: "I am a German when we win and an immigrant when we lose" (Stanley-Becker, 2018). Romelu Lukaku has written that when he plays well, newspapers refer to him as the "Belgian striker," but when he plays poorly, they refer to him as "the Belgian striker of Congolese descent" (Lukaku, 2018). Similarly, Karim Benzema, a French striker of Algerian descent, stated, "If I score, I'm French. If I don't, I'm Arab." French football great Eric Cantona summarized the French fanbases' views of the national team as follows: "When they win, they're black, white, Arab, and when they lose, they're lowlifes from the ghetto" (Beydoun, 2018). Along the same lines, Jimmy Durmaz, an Assyrian-Swedish player, suffered a torrent of racist abuse when his mistake cost Sweden a draw against Germany in the 2018 World Cup (BBC News, 2018*b*).

[17] The experiment was approved by the Stanford Institutional Review Board, protocol #47168. The design was also pre-registered with EGAP, #20181115AB.

[18] The majority of the respondents were indeed Liverpool fans. Around 85% mentioned that they follow Liverpool "Very closely" and over 98% mentioned they follow Liverpool at least "Somewhat closely."

exhausted.

The survey comprises a 2×2 factorial design experiment, in addition to a pure control group. We provided the treated respondents with a vignette emphasizing Salah's success or failure, followed by another vignette emphasizing either Salah's religiosity or "nice guy" character. The design randomly assigned respondents to the control group or to one of the following four treatment conditions:

1. Mohamed Salah is successful and religious
2. Mohamed Salah is successful and has a nice character
3. Mohamed Salah is not successful (anymore) and is religious
4. Mohamad Salah is not successful (anymore) and has a nice character

The control group is a pure control, and thus did not receive any treatment. All respondents who were not in the control condition saw the following statement, which preceded each of the vignettes: "As you probably know, Mohamed Salah is an Egyptian winger who joined Liverpool F.C. in June 2017." Each prime then included additional text, which can be found in Appendix E.1. A balance table is presented in Appendix E.2.

The outcomes of interest are three survey items that capture the extent to which the respondent believes that: (1) there is a "fundamental clash between Islam and British values," (2) immigrants "generally have a positive influence on the U.K.," and (3) the respondent has "some" or "a lot" in common with Muslims in the U.K. All of these outcomes are coded as binary in a pro-tolerant direction. We then used the first principal component generated by these items as a fourth, composite outcome (ranked on an ordinal scale).[19] The final roster of survey questions captured the following demographic covariates: city of residence, age, gender, education, favorite soccer club, and ethnicity. This roster also included placebo questions on Liverpool F.C.'s strengths, weaknesses, and evaluations of player performances.

Leveraging the factorial design of the survey experiment, we are interested in both the main and interactive effects of the treatments. We first estimate the average treatment effect (ATE) as the com-

[19]The outcomes were scaled to have mean = 0 and standard deviation = 1 for the principal component analysis. The first principal component explained 0.76 of the total variance.

parison between any active treatment cell (e.g., the success plus religiosity treatment arm), compared to the control group. Second, we estimate the main effects of each factor, which are equivalent to the average marginal component effects (AMCEs) common in the conjoint literature (Hainmueller, Hopkins and Yamamoto, 2014). The main effect is defined as the effect of a single level (e.g., the religiosity treatment), averaged over the levels of the other factor (e.g., success and failure). Because we use a convenience sample, we focus on the sample average treatment effect.

Due to randomization of the treatments, the ATE and AMCE can be estimated without bias via linear regression. We estimate the effect of each active treatment arm relative to the control by running an OLS regression of the outcome on a set of dummy variables for each of the four cells in the 2×2 factorial design. To estimate the main effects, we run two separate regressions — one for each factor — with indicators for each level within the factor. All regressions include heteroskedasticity-robust standard errors.[20]

Additionally, we examine heterogenous treatment effects by three subject attributes: (1) choosing Salah as one's favorite player, (2) residing in Liverpool, and (3) baseline empathy.[21] We leverage an incident familiar to most Liverpool F.C. (and soccer) fans to measure (3). During the 2018 UEFA Champion's League final, Liverpool F.C.'s goalkeeper, Loris Karius, committed two blunders that arguably cost his team the championship. Karius was hounded by the international media for what were seen as schoolboy errors on the world's most prestigious stage in club soccer. Fans were divided on the issue. Some stood by their keeper, referencing their club's motto of "You'll Never Walk Alone" and his sincere apology after the game. Others were less forgiving. Some referred to the German player as a Nazi and sent death threats to his home, prompting police intervention (Sky News, 2018). We use a question asking whether the respondent believes that Karius deserved the criticism he received as a measure of baseline empathy. Around 62% of respondents agreed or strongly agreed with the criticism,

[20]Due to a coding error in the survey experiment, the control group was initially much larger than the treatment groups. We corrected this survey coding error midway through data collection. However, this correction introduced the complication that not all units had equal treatment probabilities. To obtain unbiased treatment effect estimates, we weight all observations by the inverse probability of the realized treatment assignment. All the results presented here represent the weighted results unless otherwise noted.

[21]Analyses (1) and (2) are pre-registered, while (3) is an exploratory analysis aimed at capturing a novel measure of empathy.

categorized as an unempathetic response.

5.2 Results

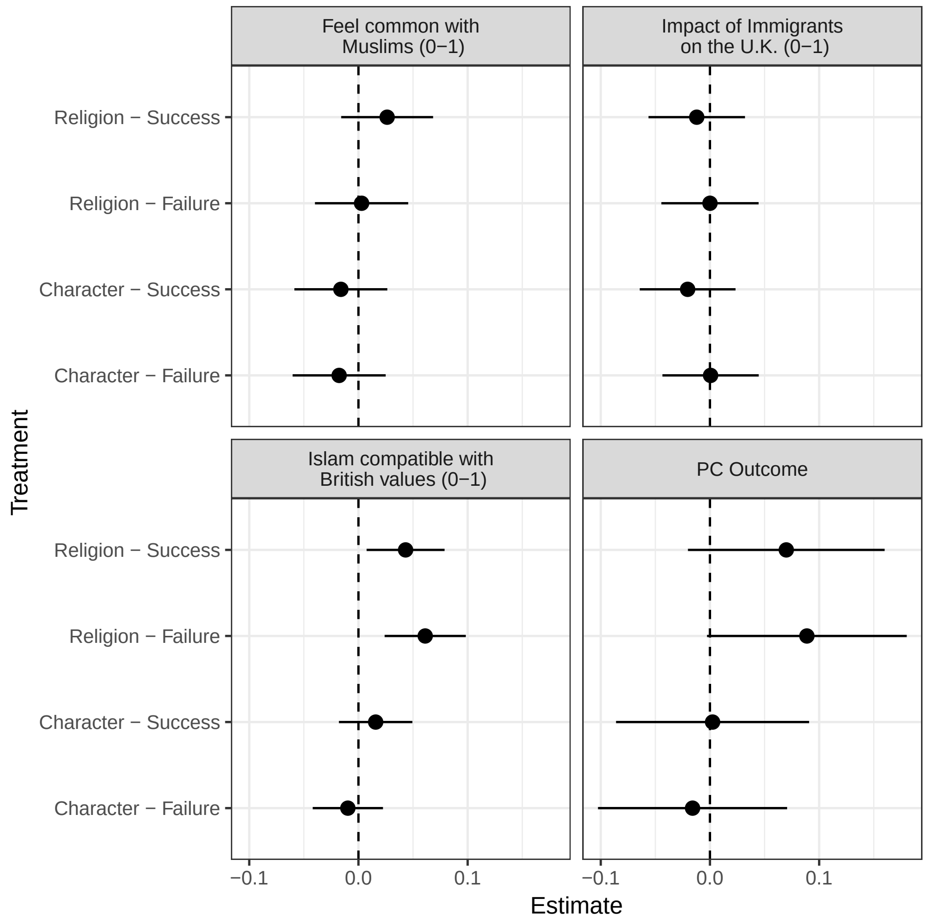


Figure 7: Coefficient Plots Representing the Average Treatment Effects on the Four Outcomes

Figure 7 shows a coefficient plot from regressions estimating the average treatment effect of each treatment the various outcome measures. We find that exposure to Salah's religiosity sparked a small, statistically significant increase in tolerant responses on the compatibility of Islam with British values outcome. Reminding respondents of Salah's Muslim identity and practices made them 4 to 6 percentage points more likely to say that Islam is compatible with British values, relative to the control group baseline of 18 percent. This effect is similar when combining the religious prime with either the success or failure vignettes (the main effects) displayed in Figure 8. Pooling across the success and failure

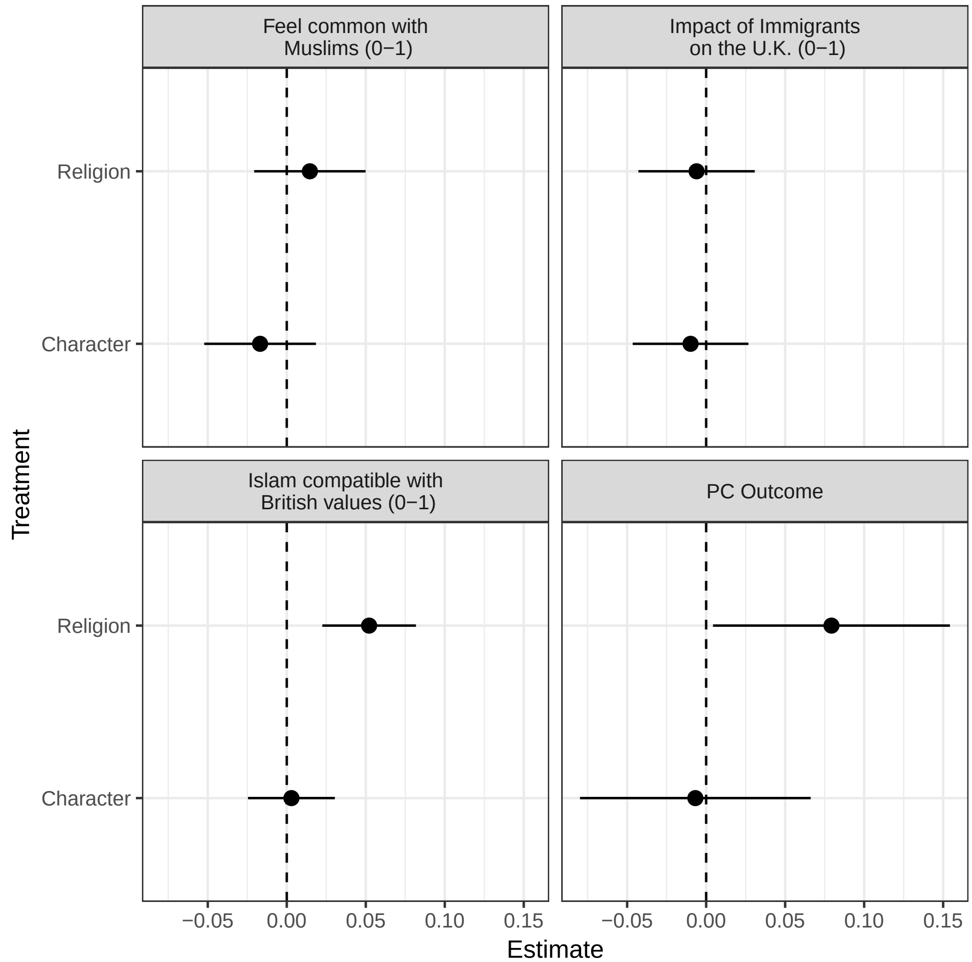


Figure 8: Main effect coefficients for religious and character treatments.

treatment arms, the religious prime led to a 5 percentage point increase in the likelihood of stating the Islam is compatible with British values, and an 8% shift on the principal component outcome. Regression results for the average treatment effect are presented in Table A-4 and results for the main effects are presented in Table A-18.

The remaining treatment arms were less effective. The character treatment arm, which primes respondents to think about Salah as a "nice guy," did not have a statistically significant effect on tolerance. The success and failure treatment arms likewise failed to shift any of the outcomes. This might signal that success and failure actually have no effect, but could also mean that it is difficult to change people's priors about Salah's performance using this simple treatment.[22] We therefore resort to another method

[22]After the treatment vignette was administered, respondents were asked "how well do you think Salah is going to

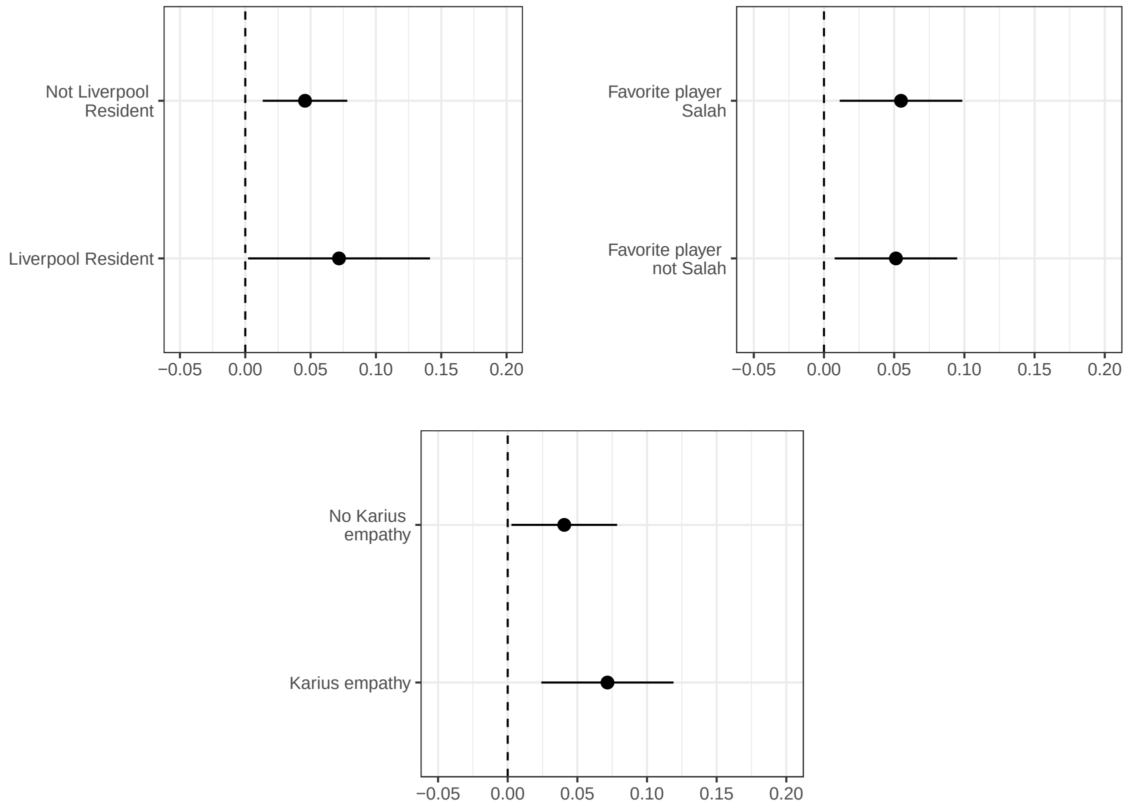


Figure 9: The points show the estimated average treatment effect on the compatibility of Islam with British values. Lines are robust 95% confidence intervals. The plot shows that a high baseline view of Salah's performance increases the effect of the religious prime.

to test the success mechanism. Specifically, we break down the survey data by whether responses were recorded one day after a Liverpool F.C. win, and by whether responses were recorded one day after Salah scored.[23] We find no systematic patterns when disaggregating results by these success metrics (Table A-25 through Table A-28). A string of poor performances by Salah and the club in the future may reveal the importance of success in shaping tolerance. Nevertheless, at the time of writing — under conditions of high baseline success — the survey results suggest that the success mechanism alone is unlikely to explain the Salah effect on Islamophobia.

play this season" and were asked to rank his performance on a scale from 1 to 10. As Figure A-8 the success and failure treatments did not influence respondents views of Salah's performance. Rivalries between Premier League fans are fierce, and fans of rival teams typically leverage the "one-season wonder" accusation at Liverpool F.C. fans, who have become somewhat accustomed to defending Salah. We thus find that fans are immune to criticisms of Salah.

[23]These tests were not pre-registered, but instead added during the analysis phase to further investigate this mechanism.

Diving deeper on the religious prime, we unpack heterogenous treatment effects by three respondent traits in Figure 9. The results suggest that there is not much heterogeneity among any of these subgroups. Empathizing with Liverpool F.C.'s former goalkeeper, Loris Karius, and living in Liverpool generates positive interactive effects, although these effects are not robust. Lastly, selecting Salah as one's favorite player has no added effect on tolerance.

6 Discussion

Our analyses demonstrate that exposure to Mohamed Salah has likely reduced hate crimes and anti-Muslim speech on Twitter among Liverpool F.C. fans. Hate crimes and anti-Muslim tweets decreased among people most exposed to Salah, relative to suitable counterfactual groups that were less exposed. These two outcomes are both costly and public, typically committed by those with high levels of prejudice. Observing such a tangible effect in this context is thus particularly compelling evidence of the effects of positive exposure, especially given that Liverpool F.C. fans reside in a city that is less ethnically diverse than the rest of England and Wales (86.2% white vs. the national average of 81.4%) and ranks in the top five counties with the highest prevalence of hate crimes (Liverpool City Council, 2011).

With regard to hate crimes, we have identified two potential explanations for the Salah effect. First, Salah's success tracks closely with the club's success. A happier fanbase may commit fewer crimes in general, including hate crimes. Yet our analysis of other types of crime undercuts this explanation. There was not a decrease in most types of crime in Merseyside after Salah was signed, relative to a synthetic control. Instead, the decrease is most pronounced when examining hate crimes.

Instead, we propose that Salah's rise may have decreased prejudice toward Muslims. Salah paints a positive image of Muslims and Islam, and his inclusion in Liverpool F.C. has contributed to lifting the club and its fans to their highest point in over a decade.[24] Few Muslims in British public life have been as open about their Muslim identity, and are as well-liked, as Salah. The public image of Salah as a hero of sorts, and the resulting normalization of some Muslim identities practices, may have dampened the

[24]Liverpool F.C.'s last major trophy was the League Cup in the 2005-06 season.

appetite for harassment and violence toward the city's Muslims. It is important to note, however, that hate crimes are fundamentally social in nature. Our evidence does not permit us to conclude that Salah reduced prejudice among bigots, necessarily. Average residents of Merseyside may have stigmatized expressions of Islamophobia after Salah's rise, without changing the underlying beliefs of bigots prone to committing anti-Muslim acts. Regardless of the mechanism, the result is observationally equivalent — a reduction in public acts of prejudice like hate crimes and hate speech.

Salah's arrival also reduced the rates of negative tweets about Islam and Muslims among Liverpool F.C. fans living in the U.K. relative to a synthetic control. This effect is partially driven by a reduction in anti-Muslim tweets among Liverpool F.C. fans. At the same time, fans of other teams appear to tweet somewhat more anti-Muslim rhetoric on Twitter following Salah's arrival. Along these lines, Salah has faced racist abuse from rival fans offline, prompting police intervention when he was called a "terrorist" and a "bomber" at games during the 2018-19 season (Al Jazeera, 2019). This result is consistent with the intergroup contact hypothesis: negative, adversarial contact tends to worsen prejudice, while a positive experience and shared goal alleviates it (Pettigrew and Tropp, 2006; Lowe, 2017; Paolini, Harwood and Rubin, 2010).

One potential threat to inference in these two event-study analyses is that there were two Islamist terrorist attacks — the Manchester Arena and London Bridge attacks — roughly one month before Salah was signed by Liverpool F.C. To verify that our hate crime results are not driven by a spike in hate crimes in these cities, we re-run the analysis but exclude London and Manchester. The hate crime results are virtually unchanged, as shown in Figure A-6. Unfortunately, these two cities contain all four large control teams in the Twitter analysis.[25] However, there is reason to think that the Twitter results are not driven by upticks in Islamophobia in these cities: the treatment effects we uncover last well beyond the terrorist attacks. The attacks would have had to cause a long-term, sustained increase in anti-Muslim tweets among just followers of London- and Manchester-based clubs to generate the patterns that we observe. This would run counter to patterns observed in studies of the effect of terror attacks on anti-Muslim tweets, which tend to spike and then re-equilibrate quickly following attacks

[25] Chelsea and Arsenal are both located in London, and Manchester United and Manchester City are of course located in Manchester.

(Magdy, Darwish and Abokhodair, 2015).

The results show that Liverpool F.C. fans (roughly approximated) engaged in less prejudicial behavior from July 2017 onwards relative to their counterparts elsewhere in the country. What about Salah could have caused this shift? The survey experiment reveals that familiarizing fans with Salah's Muslim practices had the strongest effect on attitudes toward Islam in Britain. The religious prime explains why Salah practices the way he does: that he celebrates goals with prayer, that his daughter's name is an homage to a holy city, and that he fasts during Ramadan but not on match days so as to preserve his fitness. This information is not conveyed as a series of facts, known to be an ineffective treatment in social science (Dunning et al., 2019). Instead, this information is portrayed in an empathy-inducing manner, by an individual already known to (and liked by) respondents. In agreement with the scholarship on exposure to outgroups, we argue that this information is powerful because it is both new and conveyed in a positive, personalized manner.

The median respondent to the survey is 54 years of age, high-school educated, and white. These demographics correspond to the subgroups with the most prejudiced attitudes in the country (The Migration Observatory at Oxford University, 2011). It is probable that most respondents lack accurate information about Islam (although we do not measure baseline knowledge directly), and would thus benefit the most from the information provided by positive exposure. The success/failure treatment focusing on Salah's season statistics may not provide new information to the average respondent (85% of whom follow Liverpool "very closely"), although we cannot rule out that success is a necessary condition for Salah effects to unfold. The character prime is also devoid of new information: Salah's agreeable personality comes through during games even to casual fans (Oliver, 2019). The religion prime is the only treatment to provide novel information, a necessary (but insufficient) condition for informational interventions to work (Lieberman, Posner and Tsai, 2014). Importantly, information communicated via intergroup exposure is also better-suited to build tolerance relative to objective statements of fact. It is logical that the compatibility outcome is most susceptible to an information treatment: information about Islam is better poised to change attitudes about Islamic values as opposed to attitudes about immigrants or British Muslims.

How generalizable are these results? We suggest that exposure will reduce prejudice in a manner consistent with the Salah effect when coverage of a celebrity, public figure, or high-profile role model provides novel information about an outgroup and is positive. With regard to the first condition, we expect positive exposure to be most effective when it conveys new information about members of an outgroup where previously there was little or inaccurate information. This might be more likely to occur when people gain information about members of a relatively new or unknown outgroup, such as a newly arrived cohort of immigrants, or in societies marked by residential segregation and little outgroup exposure. Although not necessarily the case, novel information can often be counter-stereotypical.

With regard to second condition, celebrities are often inundated with media attention covering their personal and professional lives, but this coverage is not always positive. For example, celebrities may take controversial political stances that stoke negative attention and exacerbate prejudice among some fans. Colin Kaepernick exemplifies this scenario. A young African-American quarterback, he started in two conference championship games and one Super Bowl in his most recent five seasons, and has one of the best touchdown-to-interceptions ratio in NFL history. Yet, he has been unsigned for three years (at the time of writing) for kneeling during the American national anthem in protest of racial injustice. Teams have backed down during subsequent negotiations, reportedly in fear of a backlash from (mostly white) fans (Reid, 2017). In this way, taking a stance on minority-specific political issues (e.g., prejudice or racial injustice) may fuel negative media coverage, thereby decreasing the likelihood and efficacy of positive exposure. Note that taking such stances also fails to reveal new information about the outgroup, undermining our first condition.

Even in the absence of controversial political stances, or scandalous behavior, media outlets can project their own biases in their coverage. Right-wing tabloids do not always need an excuse to portray some public figures negatively. Consider the following *Daily Mail* headlines, covering two players — the first black, the second white — of the same age and playing for the same club, for making a similar purchase, ten months apart: "Young Manchester City footballer, 20, on 25,000 a week splashes out on mansion on market for £2.25 million despite having never started a Premier League match" (Herbert, 2018) vs. "Manchester City starlet Phil Foden buys new £2 million home for his mum"

(Joseph, 2018). Some elements of the British press have reported on the Duchess of Cambridge Meghan Markle in a similarly negative, and allegedly racialized, manner (Garcia-Navarro, 2019). Valence of media coverage seems to be partly a function of a celebrity's political positions, behavior off the field, and the outlet's ideological leanings, but remains hard to predict.

Salah meets the conditions under which we would expect positive exposure to work especially well. His actions on and off the field have provided fans with new information about Muslims and Islam, meeting the novelty of information condition. Salah popularized Islamic prayer on the field — a celebration fans have now seen over 50 times. His open devotion to his faith has familiarized fans with Islamic beliefs, identities, and practices. Unlike many other elite athletes, he has also managed to avoid scandal and close scrutiny of his personal life. Salah is also fortunate in that the media have generally refrained from framing his private actions negatively, meeting our positive information condition. The British press tends to report positively and prolifically on Salah as a result of his tremendous success and perhaps because he has avoided political commentary and personal scandal. Lastly, Salah's frequent displays of religiosity make it likely that he is seen as typical of Muslims at large, allowing viewers to infer information about the outgroup without viewing him as an exception (Rothbart and John, 1985).

Demonstrating the potential generalizability of the Salah effect, another Liverpool F.C. player deserves a mention: Sadio Mané. Mané is a Senegalese Muslim who joined the squad exactly one year before Salah, who also demonstrates his religiosity to fans on occasion. Mané is not as heavily covered by the international nor local media, however, when compared with his Egyptian teammate. Scraping headlines of Liverpool's most widely circulated newspaper, *The Liverpool Echo*, we find that Mané's signing captured around 3% of headlines relative to Salah's 9% (Figure A-2). Accordingly, we find no "Mané effect" on hate crimes when constraining the study period to the pre-Salah era, and taking the date of Mané's signing (July 2016) as the relevant time break (Table A-1 and A-5). We do, however, find a Mané effect on anti-Muslim tweets similar in magnitude to the Salah effect (Figure A-4). Recall that the Twitter analysis focuses only on soccer fans, who are more likely to be familiar with a less publicized player like Mané. We take this as suggestive evidence that positive exposure seems to have reduced anti-Muslim speech in the case of Mané as well — a player who meets the scope conditions discussed above — and that these effects correlate with the intensity of exposure.

7 Conclusion

Exposure to celebrities, including writers, artists, athletes, and reality TV stars, has become a quotidian feature of modern life both online and through traditional media channels. Despite this, we know relatively little about how these public figures may influence social attitudes and behaviors. We take a first step in quantifying the effect of exposure to a successful celebrity from a stigmatized group on prejudiced attitudes and behavior. By assessing the effect of Liverpool F.C. star Mohamed Salah on Islamophobia, we offer an arguably difficult test of exposure to outgroups: male fans of a sport with an on-going problem with racist hooliganism. Our results suggest that positive exposure to famous members of an outgroup can mitigate prejudiced attitudes and behaviors, potentially through the provision of new information delivered in an empathy-inducing manner. We hope that future work can exploit a similar design to explore the impact of other minority public figures — in diverse contexts — on prejudice. Such work will help us to better assess the scope conditions of the Salah effect and offer new potential avenues for building social cohesion around the globe.

References

Abadie, Alberto, Alexis Diamond and Jens Hainmueller. 2010. "Synthetic Control Methods for Comparative Case Studies : Estimating the Effect of California's Tobacco Control Program." *Journal of the American Statistical Association* 105(490):493–505.

Adida, Claire L, Adeline Lo and Melina R Platas. 2018. "Perspective taking can promote short-term inclusionary behavior toward Syrian refugees." *Proceedings of the National Academy of Sciences* 115(38):9521–9526.

Al Jazeera. 2019. "West Ham investigates 'racist abuse' of footballer Mohamed Salah." *Al Jazeera* .
URL: *https://www.aljazeera.com/news/2019/02/west-ham-investigates-racist-abuse-footballer-mohamed-salah-190206154256815.html*

Al-Sayyad, Yasmine. 2018. "Liverpool F.C.'s Mohamed Salah, an Arab Muslim Sports Star Subtly Confronting Racism and Islamophobia." *New Yorker* .
URL: *https://www.newyorker.com/sports/sporting-scene/liverpool-fcs-mohamed-salah-an-arab-muslim-sports-star-subtly-confronting-racism-and-islamophobia*

Allport, Gordon W. 1979. *The Nature of Prejudice*. 25 ed. Cambridge, Massachusetts: Perseus Books Publishing, L.L.C.

Aly, Remona. 2015. "Nadiya Hussain has won so much more than the Great British Bake Off." *The Guardian* .
URL: *https://www.theguardian.com/commentisfree/2015/oct/08/nadiya-hussain-has-won-so-much-more-than-the-great-british-bake-off*

Athey, Susan, Mohsen Bayati, Nikolay Doudchenko, Guido Imbens and Khashayar Khosravi. 2018. "Matrix completion methods for causal panel data models.".

Barnhardt, Sharon. 2009. "Near and Dear? Evaluating the Impact of Neighbor Diversity on Inter-Religious Attitudes." *Unpublished Working Paper* .
URL: *http://research.economics.unsw.edu.au/gbose/DevWorkshop/papers/Barnhardt_near_and_dear_paper.pdf*

Batson, C. Daniel, Johee Chang, Ryan Orr and Jennifer Rowland. 2002. "Empathy, attitudes, and action: Can feeling for a member of a stigmatized group motivate one to help the group?" *Personality and Social Psychology Bulletin* 28(12):1656–1666.

BBC News. 2018*a*. "Religious hate crimes: Rise in offences recorded by police." *BBC News* .
URL: *https://www.independent.co.uk/sport/football/premier-league/kashif-siddiqi-interview-premier-league-kashif-siddiqi-foundation-altus-league-a8283736.html*

BBC News. 2018*b*. "World Cup 2018: Sweden's Jimmy Durmaz says racial abuse 'passed limit'." *BBC News* .
URL: *https://www.bbc.com/sport/football/44593545*

Benoit, Kenneth, Drew Conway, Benjamin E Lauderdale, Michael Laver and Slava Mikhaylov. 2016. "Crowd-sourced text analysis: Reproducible and agile production of political data." *American Political Science Review* 110(2):278–295.

Beydoun, Khaled A. 2018. "Standing with Trevor Noah: a World Cup for France is a win for Africa too." *The Guardian* .
URL: *https://www.theguardian.com/commentisfree/2018/jul/22/trevor-noah-world-cup-france-africa*

Borden, Sam. 2014. "The Friendly Derby? Well, Everton-Liverpool Is Friendlier." *The New York Times* .
URL: *https://www.nytimes.com/2014/01/28/sports/soccer/the-friendly-derby-well-everton-liverpool-is-friendlier.html*

Broockman, David and Joshua Kalla. 2016. "Durably reducing transphobia: A field experiment on door-to-door canvassing." *Science* 352(6282):220–224.

Burns, Justine, Lucia Corno and Eliana La Ferrara. 2015. "Interaction, Prejudice and Performance. Evidence from South Africa." *Unpublished Working Paper* .
URL: *https://bit.ly/30T51z1*

Calzo, Jerel P and L Monique Ward. 2009. "Media exposure and viewers' attitudes toward homosexuality: Evidence for mainstreaming or resonance?" *Journal of Broadcasting & Electronic Media* 53(2):280–299.

Carrell, Scott E, Mark Hoekstra and James E West. 2015. "The Impact of Intergroup Contact on Racial Attitudes and Revealed Preferences." *National Bureau of Economic Research* (No. w20940).
URL: *http://www.nber.org/papers/w20940*

Crisp, Richard J and Rhiannon N Turner. 2009. "Can imagined interactions produce positive perceptions? Reducing prejudice through simulated social contact." *American Psychologist* 64(4):231.

Doudchenko, Nikolay and Guido W. Imbens. 2016. "Balancing, regression, difference-in-differences and synthetic control methods: A synthesis." *National Bureau of Economic Research* (No. w22791).
URL: *https://www-nber-org.stanford.idm.oclc.org/papers/w22791.pdf*

Dunning, Thad, Guy Grossman, Macartan Humphreys, Susan D. Hyde, Craig McIntosh and Gareth Nellis. 2019. *Information, Accountability, and Cumulative Learning: Lessons from Metaketa I*. Cambridge University Press.

Elahi, Farah and Omar Khan. 2017. "Islamophobia: Still a challenge for us all." *Runnymede Trust* .
URL: *https://bit.ly/2K9SXDI*

Enos, Ryan D. 2014. "Causal effect of intergroup contact on exclusionary attitudes." *Proceedings of the National Academy of Sciences* 111(10):3699–3704.

Garcia-Navarro, Lulu. 2019. "Inside the Racist Online Attacks On Meghan Markle." *National Public Radio* .
URL: *https://www.npr.org/2019/03/10/701987112/inside-the-racist-online-attacks-on-meghan-markle*

Hainmueller, Jens, Daniel J. Hopkins and Teppei Yamamoto. 2014. "Causal Inference in Conjoint Analysis: Understanding Multidimensional Choices via Stated Preference Experiments." *Political Analysis* 22:1–30.

Hangartner, Dominik, Elias Dinas, Moritz Marbach, Konstantinos Matakos and Dimitrios Xefteris. 2019. "Does Exposure to the Refugee Crisis Make Natives More Hostile?" *American Political Science Review* 113(2):442–455.

Heath, Anthony and Richards Lindsay. 2016. "Attitudes towards immigration and their antecedents: Topline results from round 7 of the European social survey.".
URL: *https://www.europeansocialsurvey.org/docs/findings/ESS7_toplines_issue_7_immigration.pdf*

Hecht, Brent, Lichan Hong, Bongwon Suh and Ed H Chi. 2011. Tweets from Justin Bieber's heart: the dynamics of the location field in user profiles. In *Proceedings of the SIGCHI conference on human factors in computing systems*. ACM pp. 237–246.

Herbert, Ian. 2018. "Manchester City starlet Phil Foden buys new £2m home for his mum." *The Daily Mail* .
URL: *https://www.dailymail.co.uk/news/article-5253633/Man-City-footballer-20-25k-week-buys-market-2-25m-home.html*

Hutchison, Paul and Harriet E S Rosenthal. 2011. "Prejudice against Muslims: Anxiety as a mediator between intergroup contact and attitudes, perceived group variability and behavioural intentions." *Ethnic and Racial Studies* 34(1):40–61.

Joseph, Anthony. 2018. "Young Manchester City footballer, 20, on £25,000 a week splashes out on mansion on market for £2.25million despite having never started a Premier League match." *The Daily Mail* .
URL: *https://www.dailymail.co.uk/news/article-5253633/Man-City-footballer-20-25k-week-buys-market-2-25m-home.html*

Joyce, Nick and Jake Harwood. 2014. "Improving intergroup attitudes through televised vicarious intergroup contact: Social cognitive processing of ingroup and outgroup information." *Communication Research* 41(5):627–643.

Khattab, Nabil and Ron Johnston. 2015. "Ethno-religious identities and persisting penalties in the UK labor market." *The Social Science Journal* 52(4):490–502.

Lemmer, Gunnar and Ulrich Wagner. 2015. "Can we really reduce ethnic prejudice outside the lab? A meta-analysis of direct and indirect contact interventions." *European Journal of Social Psychology* 45(2):152–168.

Lieberman, Evan S, Daniel N Posner and Lily L Tsai. 2014. "Does information lead to more active citizenship? Evidence from an education intervention in rural Kenya." *World Development* 60:69–83.

Liverpool City Council. 2011. Census summary. Technical report.
URL: *https://liverpool.gov.uk/council/key-statistics-and-data/census/census-summary/*

Lowe, Matt. 2017. "Types of Contact: A Field Experiment on Collaborative and Adversarial Caste Integration." *MIT Working Paper* .

Lukaku, Romelu. 2018. "I've Got Some Things to Say." *The Players Tribune* .
URL: *https://www.theplayerstribune.com/en-us/articles/romelu-lukaku-ive-got-some-things-to-say*

Magdy, Walid, Kareem Darwish and Norah Abokhodair. 2015. "Quantifying public response towards Islam on Twitter after Paris attacks." *Unpublished Manuscript* .
URL: *https://arxiv.org/abs/1512.04570*

Mcleod, Maurice. 2013. "Theresa May's immigration bill is a valuable tool for racist landlords." *The Guardian* .
URL: *https://www.theguardian.com/commentisfree/2013/oct/15/theresa-may-immigration-bill-racist-landlords*

Mislove, Alan, Sune Lehmann, Yong-Yeol Ahn, Jukka-Pekka Onnela and J Niels Rosenquist. 2011. Understanding the demographics of twitter users. In *Fifth international AAAI conference on weblogs and social media*.

Monks, Kieron. 2018. "Mohamed Salah's greatest legacy may be off the pitch." *Middle East Eye* .

Office, Home. 2012. Hate crimes, England and Wales 2011 to 2012. Technical report.
URL: *https://www.gov.uk/government/publications/hate-crimes-england-and-wales-2011-to-2012--2/hate-crimes-england-and-wales-2011-to-2012*

Oliver, John. 2019. "Mohamed Salah." *TIME Magazine* .
URL: *http://time.com/collection/100-most-influential-people-2019/5567841/mohamed-salah/*

Paluck, Elizabeth Levy, Seth Green and Donald P Green. 2018. "The contact hypothesis re-evaluated." *Behavioural Public Policy* pp. 1–30.

Paolini, Stefania, Jake Harwood and Mark Rubin. 2010. "Negative intergroup contact makes group memberships salient: Explaining why intergroup conflict endures." *Personality and Social Psychology Bulletin* 36(12):1723–1738.

Pettigrew, Thomas F. 1998. "Intergroup contact theory." *Annual Review of Psychology* 49(1):65–85.

Pettigrew, Thomas F and Linda R Tropp. 2006. "A meta-analytic test of intergroup contact theory." *Journal of personality and social psychology* 90(5):751.

Pitkin, Hanna F. 1967. *The concept of representation*. Vol. 75 University of California Press.

Rao, Gautam. 2019. "Familiarity Does Not Breed Contempt: Diversity, Discrimination and Generosity in Delhi Schools." *American Economic Review* 109(3):774–809.

Reid, Jason. 2017. "We may have seen the last of Colin Kaepernick in the NFL." *The Undefeated* .
URL: *https://theundefeated.com/features/we-may-have-seen-the-last-of-colin-kaepernick-in-the-nfl/*

Reyes Jr., Ruben E. 2018. "Queer Eye for the Small-Minded Guy." *The Harvard Crimson* .
URL: *https://www.thecrimson.com/column/pop-cultural/article/2018/7/25/reyes-queer-eye/*

Rothbart, Myron and Oliver P John. 1985. "Social categorization and behavioral episodes: A cognitive analysis of the effects of intergroup contact." *Journal of Social Issues* 41(3):81–104.

Sands, Melissa L. 2017. "Exposure to inequality affects support for redistribution." *Proceedings of the National Academy of Sciences* 114(4):663–668.

Scacco, Alexandra and Shana S Warren. 2018. "Can social contact reduce prejudice and discrimination? Evidence from a field experiment in Nigeria." *American Political Science Review* pp. 1–24.

Schwartz, Larry. 1999. "Jackie changed face of sports." *ESPN* .
URL: *https://www.espn.com/sportscentury/features/00016431.html*

Sedhi, Ami. 2004. "UK Census: religion by age, ethnicity and country of birth." *The Guardian* .
URL: *https://www.theguardian.com/news/datablog/2013/may/16/uk-census-religion-age-ethnicity-country-of-birth*

Simonivitz, Gabor, Gabor Kezdi and Peter Kardos. 2018. "Seeing the World Through the Other's Eye: An Online Intervention Reducing Ethnic Prejudice." *American Political Science Review* 112(1):186–193.

Siregar, Cady. 2018. "World Cup Ramadan: How Salah, Pogba & more are preparing for Russia 2018." *Goal* .
URL: *https://www.goal.com/en-us/news/world-cup-ramadan-how-salah-pogba-more-are-preparing-for/1n12b9uxyxu9516ti8dmmjz1c6*

Sky News. 2018. "Liverpool goalkeeper Loris Karius sent death threats after Champions League blunders.".
URL: *https://news.sky.com/story/liverpool-goalie-loris-karius-sent-death-threats-after-champions-league-blunders-11386990*

Sloan, Luke. 2017. "Who Tweets in the United Kingdom? Profiling the Twitter Population Using the British Social Attitudes Survey 2015." *Social Media+ Society* 3(1):1–11.

Social Backers. 2019. United Kingdom Social Marketing Reports. Technical report.
URL: *https://www.socialbakers.com/statistics/twitter/profiles/united-kingdom/*

Stanley-Becker, Isaac. 2018. “Mesut Ozil: World Cup player says he is ‘a German when we win’ but ‘an immigrant when we lose,’ quits national team.” *The Washington Post* .
URL: *https://www.washingtonpost.com/news/morning-mix/wp/2018/07/23/quitting-national-team-world-cup-player-says-he-is-a-german-when-we-win-but-an-immigrant-when-we-lose/*

Steinmayr, Andreas. 2016. “Exposure to refugees and voting for the far-right:(unexpected) results from Austria.” *IZA DP* (No.9790).
URL: *http://ftp.iza.org/dp9790.pdf*

Stephan, Walter G and Cookie W Stephan. 1984. “The role of ignorance in intergroup relations.” *Groups in Contact: The Psychology of Desegregation* pp. 229–255.

Stevenson, Jacqueline, Sean Demack, Bernie Stiell, Muna Abdi, Lisa Clarkson, Farhana Ghaffar and Shaima Hassan. 2017. “The Social Mobility Challenges Faced by Young Muslims.” *Social Mobility Commission* .
URL: *https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/642220/Young_Muslims_SMC.pdf*

Tell Mama. 2017. Beyond the Incident: Outcomes for Victims of Anti-Muslim Prejudice. Technical report.
URL: *https://tellmamauk.org/wp-content/uploads/2018/07/Tell-MAMA-Report-2017.pdf*

The Migration Observatory at Oxford University. 2011. “UK Public Opinion toward Migration: Determinants of Attitudes.” https://migrationobservatory.ox.ac.uk/resources/briefings/uk-public-opinion-toward-migration-determinants-of-attitudes/.

The National. 2018. “Footballer Mo Salah is tackling Islamophobia head-on.”.
URL: *https://www.thenational.ae/opinion/editorial/footballer-mo-salah-is-tackling-islamophobia-head-on-1.724010*

Thomas, Andi. 2018. “Soccer star Mo Salah’s massive popularity is changing perceptions of Muslims in the UK.” *Vox.com* .
URL: *https://www.vox.com/world/2018/6/15/17433822/mo-salah-liverpool-injury-egypt-2018-world-cup-muslim-islam*

Todd, Andrew R and Adam D Galinsky. 2014. “Perspective-taking as a strategy for improving intergroup relations: Evidence, mechanisms, and qualifications.” *Social and Personality Psychology Compass* 8(7):374–387.

Triandis, Harry Charalambos. 1994. *Culture and social behavior*. New York: McGraw-Hill.

Weber, Renee and Jennifer Crocker. 1983. “Cognitive processes in the revision of stereotypic beliefs.” *Journal of personality and social psychology* 45(5):961.

Wiseman, Eva. 2018. “Nadiya Hussain: ‘This is more than a job – it’s important to be out there’.” *The Guardian* .

URL: *https://www.theguardian.com/food/2018/dec/16/nadiya-hussain-bake-off-winner-this-is-more-than-a-job*

Xu, Yiqing. 2017. "Generalized Synthetic Control Method: Causal Inference with Interactive Fixed Effects Models." *Political Analysis* 25:57–76.

Online Appendix for "Can Celebrities Reduce Prejudice?"

Contents

A Google Trends Data

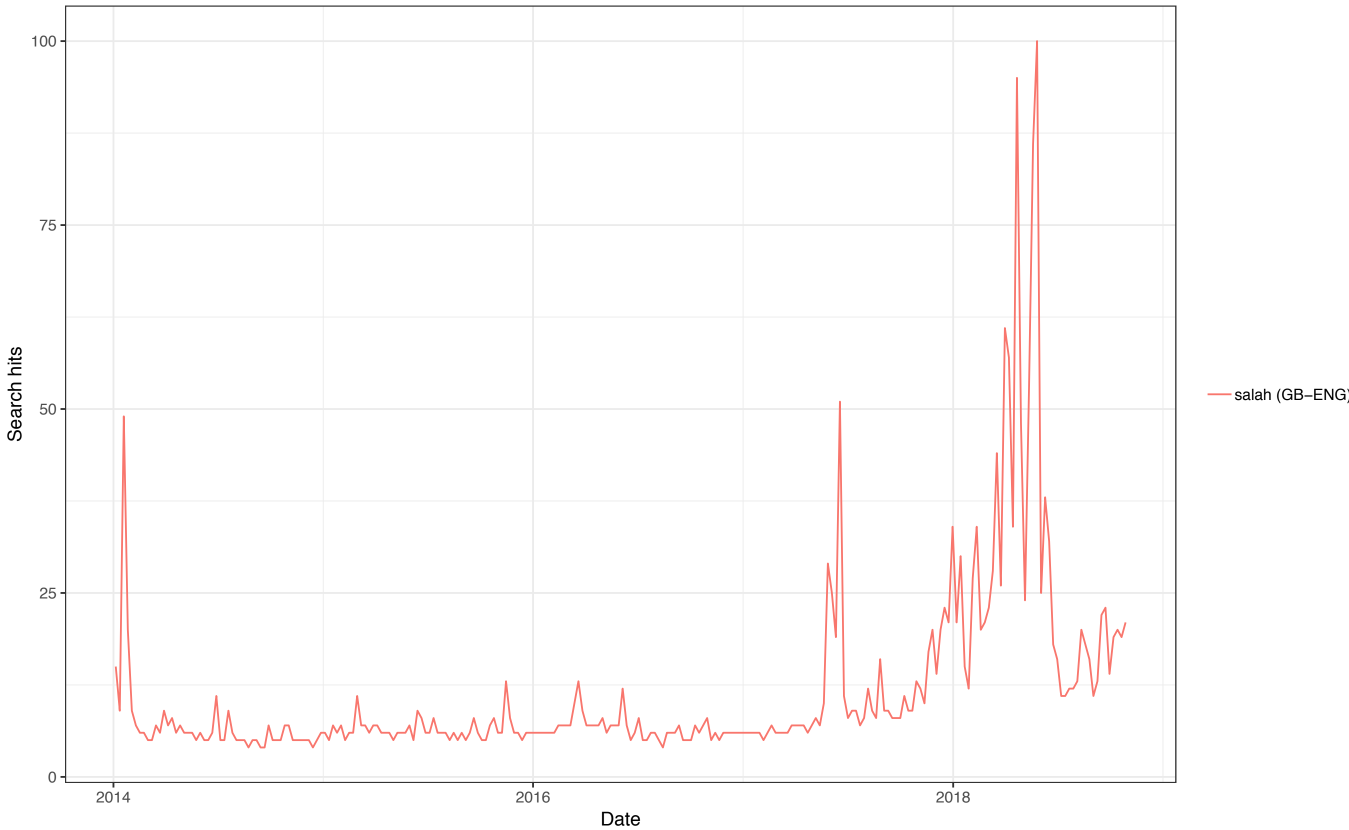


Figure A-1: Normalized Google Searches for ”Salah” in the UK (2014-2018)

B Mané Effect Analysis

B.1 Liverpool Echo

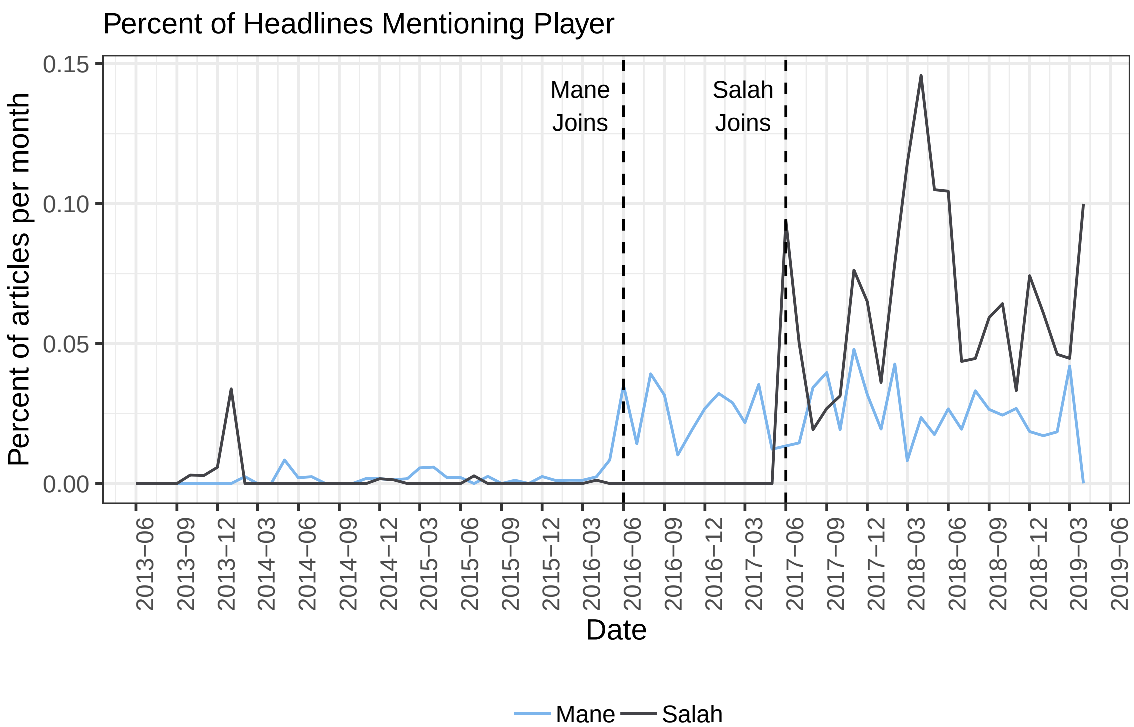


Figure A-2: Percent of monthly titles in Liverpool Echo that mention Mané or Salah

B.2 Hate Crimes

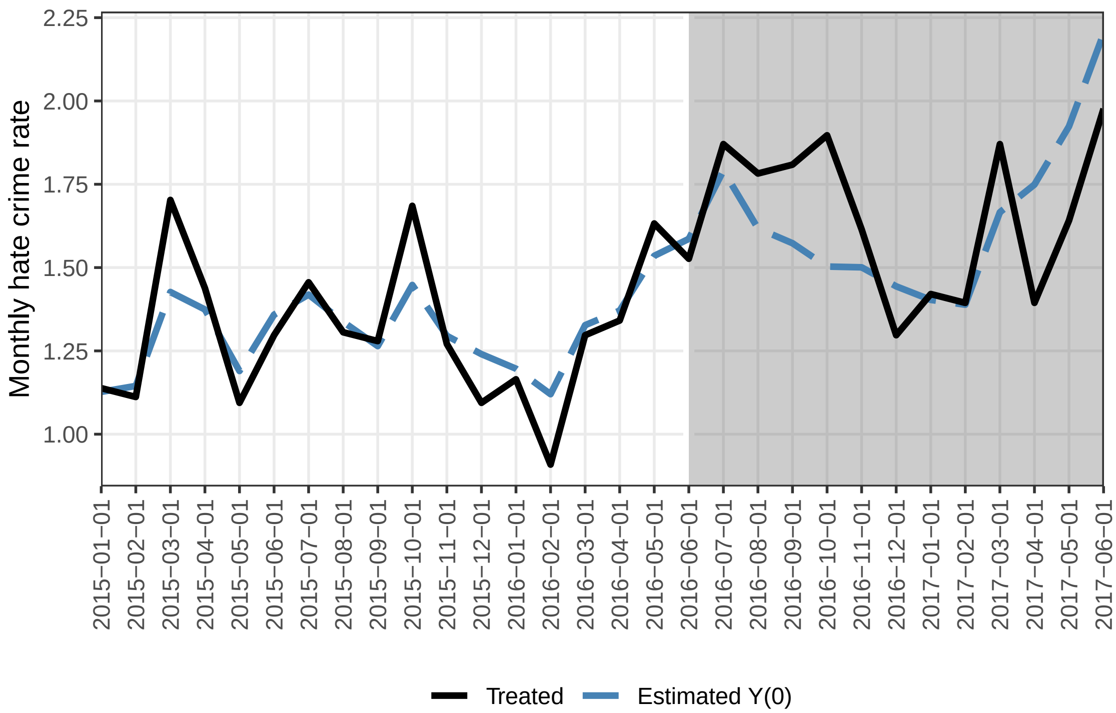
Here, we repeat the same matrix completion analysis of hate crime data as in the main text, except treating July 2016 — the month in which Sadio Mané signed with Liverpool — as the beginning of treatment. Additionally, to avoid picking up the Salah effect, we truncate the data to before Salah signed.

The results are shown in Figure A-3. Overall, we see no consistent difference between observed and imputed hate crimes in Merseyside after Mané joined Liverpool (but before Salah joined). Averaging across post-treatment months, the estimated ATT is 0.017 (S.E. $= 0.049$), which corresponds to a 1.3% *increase* in the hate crime rate — though this result is not statistically significant.

B.3 Twitter

We also repeat the same matrix completion analysis of Twitter data as in the main text, except treating July 2016 — the month in which Sadio Mané signed with Liverpool — as the beginning of treatment. Additionally, to avoid picking up the Salah effect, we truncate the data to before Salah signed.

(a) Observed and imputed outcomes for Merseyside



(b) Estimated ATT in every period

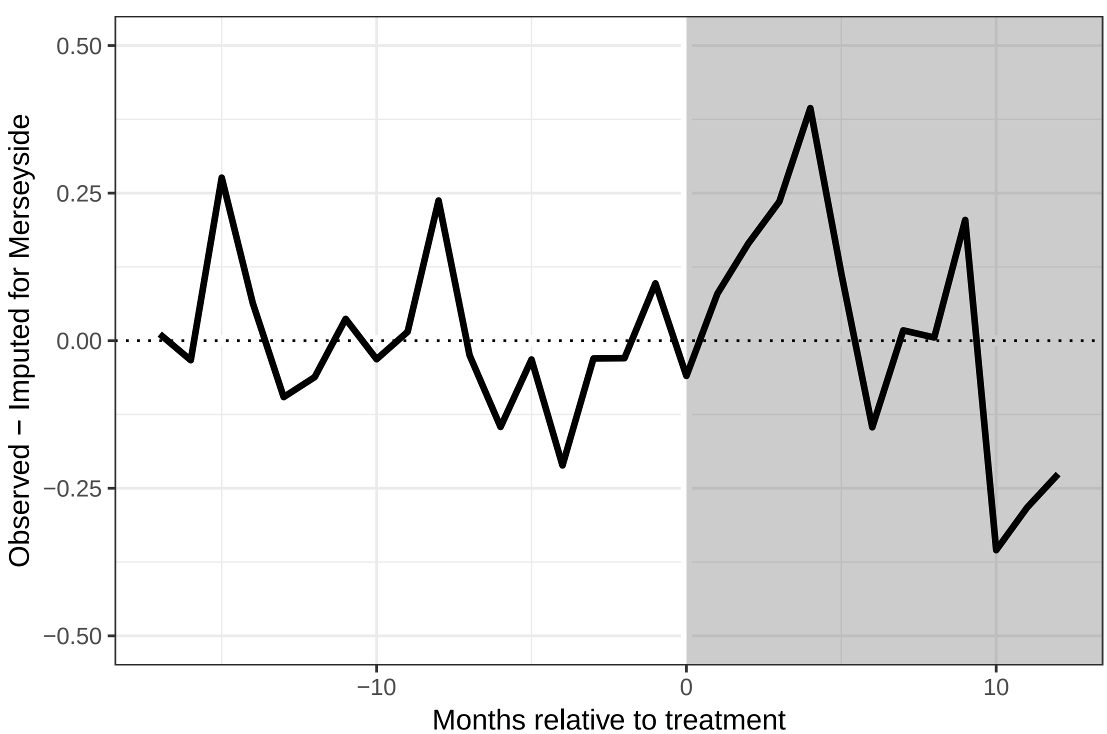
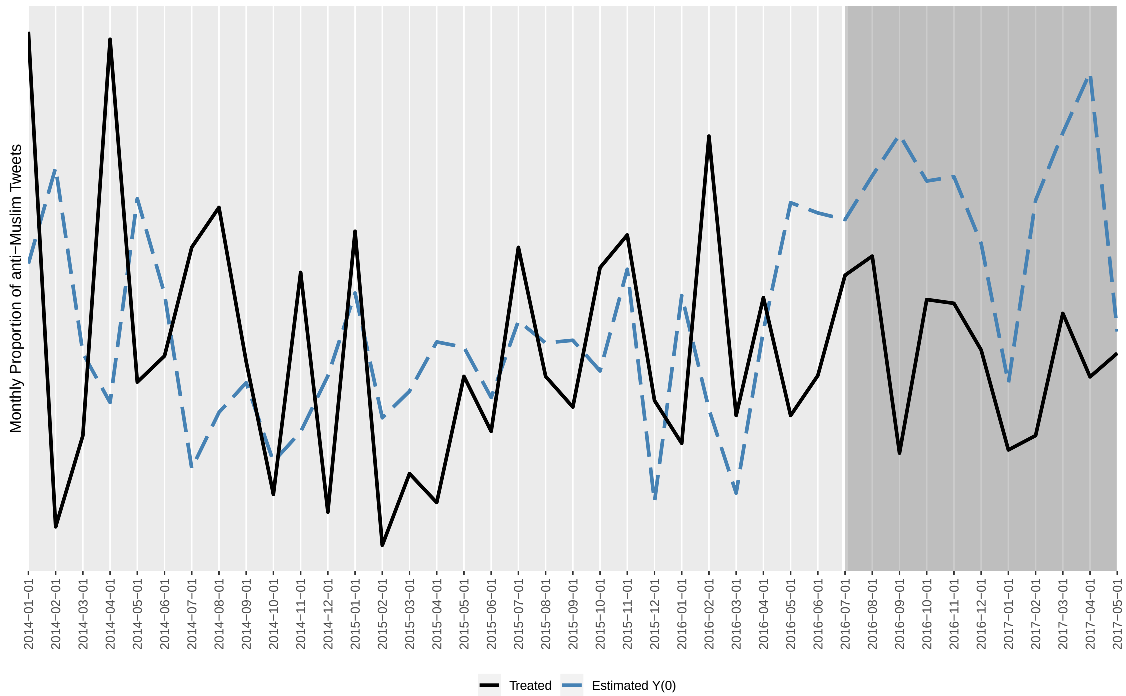


Figure A-3: Matrix completion results, treating Sadio Mané's signing as the beginning of treatment. The top panel shows the observed (solid line) and imputed (dashed line) monthly hate crime rates in Merseyside. The bottome panel shows the difference between the observed and imputed outcomes. In the post-treatment period, this is the estimate of the ATT.

The results are shown in Figure A-4. Unlike the hate crime data, here we do observe a significant decrease between observed and imputed hate crimes in Merseyside after Mané joined Liverpool (but before Salah joined). Averaging across post-treatment months, the estimated ATT is -0.043 (S.E. $=$ 0.007), which corresponds to a 59.8% *decrease* in the proportion of anti-Muslim tweets.

(a) Observed and imputed outcomes for Merseyside



(b) Estimated ATT in every period

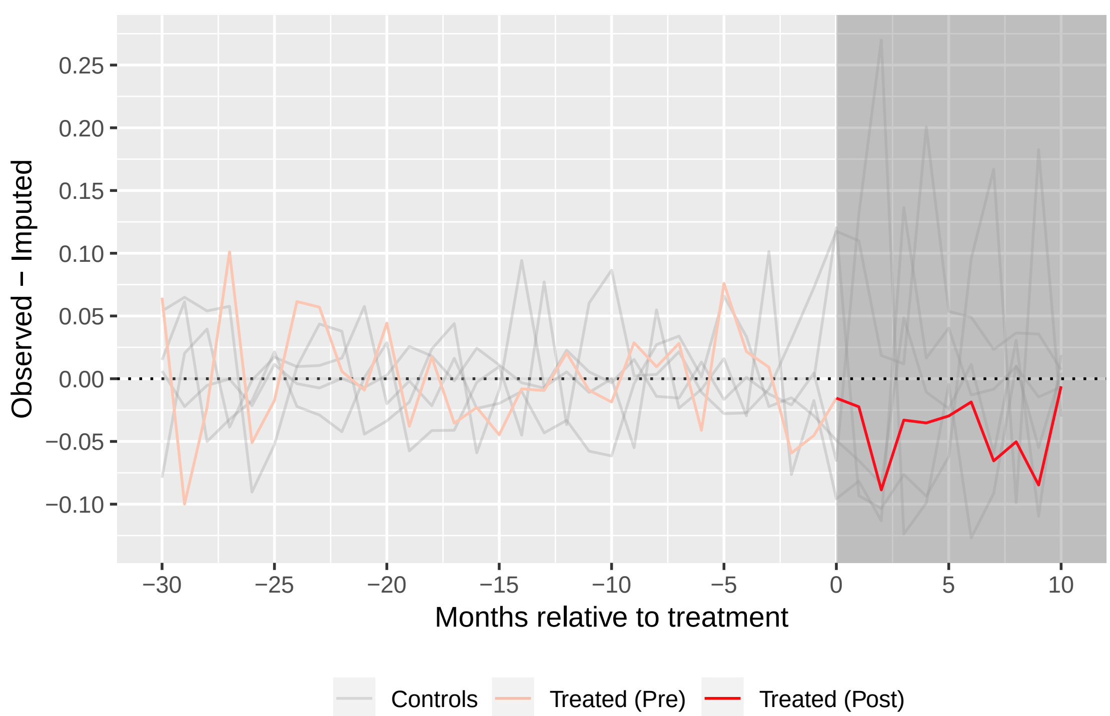


Figure A-4: Matrix completion results, treating Sadio Mané's signing as the beginning of treatment. The top panel shows the observed (solid line) and imputed (dashed line) monthly proportion of anti-Muslim tweets produced by Liverpool fans. The bottom panel shows the difference between the observed and imputed outcomes in Liverpool fans' tweets (red line) relative to tweets produced by fans of other U.K. football clubs (gray lines). In the post-treatment period, this is the estimate of the ATT.

C Additional Hate Crime Analysis

C.1 Generalized Diff-in-Diff

An alternative method of measuring the effect of Salah on hate crimes is to employ a generalized difference-in-differences framework by estimating a two-way fixed-effects (2WFE) regression of the form

$$Y_{it} = \tau D_{it} + \delta_i + \gamma_t + \epsilon_{it}, \tag{A-1}$$

where D_{it} is an indicator that switches on for Merseyside in the post-treatment period, δ_i and γ_t are unit and month fixed effects, respectively, and ϵ_{it} is a mean-zero error term. In this framework, given parallel trends for the treated and untreated units in the absence of treatment, τ is the the ATT.

Table A-1 presents the main regression results. The first column reports the plain 2WFE model, the second adds county-specific linear time trends, and the third and fourth add population weights. All specifications give similar results, showing that there was a decrease in the hate crime rate in Merseyside after Salah was signed. The estimates are in the range of -0.2, which is very similar to the estimated ATT yielded by the matrix completion method, which was -0.275.

In all the regression models, the estimates appear to be significant. However, with only a single treated unit, the standard errors may not be reliable due to the Behrens-Fisher problem. We therefore undertake an alternative form of inference, whereby we randomly assign a single unit to be treated, with treatment beginning in a randomly chosen month that is at least 4 months after the first observations in our dataset and as late as the actual treatment month. We then estimate the 2WFE specification in column (1) of Table A-1. We repeat this procedure 10,000 times to generate a null distribution of the parameter estimate. We then compute a p-value by calculating the proportion of simulated coefficient estimates that are at least as small as the actual observed estimate.

The result of this exercise is presented in Figure A-5, which shows a histogram of the null distribu-

	(1)	(2)	(3)	(4)
Treated	-0.296^{***}	-0.214^{***}	-0.288^{***}	-0.152^{*}
	(0.0610)	(0.0488)	(0.0903)	(0.0805)
Observations	969	969	969	969
R-squared	0.896	0.932	0.913	0.942
County FE	✓	✓	✓	✓
Month FE	✓	✓	✓	✓
Unit-specific time trend		✓		✓
Weights			✓	✓

Table A-1: Regression results with monthly annualized hate crime rate as the dependent variable. Robust standard errors, clustered by county, are reported in parentheses. For comparison, the estimated ATT yielded by the matrix completion method, averaging across post-treatment months, was -0.275. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

tion generated using the placebo approach described above. The vertical line shows the actual estimate reported in column (1) of Table A-1. The estimated one-sided p-value is 0.139. In other words, roughly 13% of simulations generated a point estimate less than -0.296. We interpret this to be weak evidence in favor of the Salah effect hypothesis.

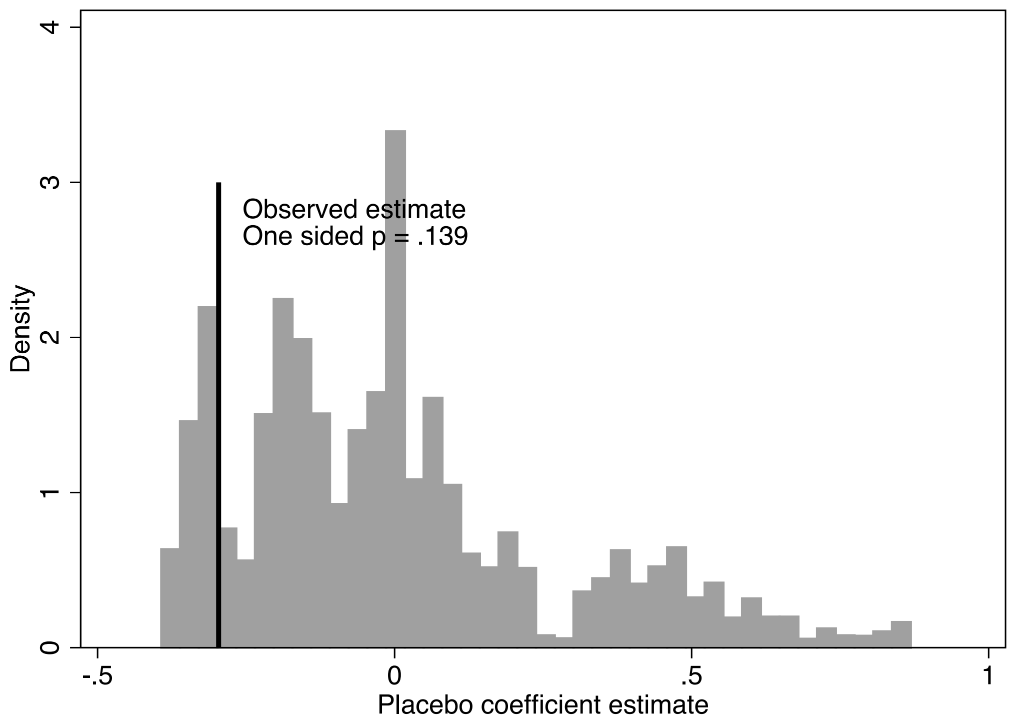


Figure A-5: The histogram shows the simulated null distribution of difference-in-differences estimates. The solid black line shows the observed coefficient for Merseyside. The one-sided p-value is 0.139.

C.2 Are London and Manchester Driving the Results?

As noted in Section 6, there were two terrorist attacks just prior to Salah joining Liverpool F.C. — one in Manchester and one in London. To confirm that our results are not being driven by an increase in hate crimes in these cities in response to the attacks, we re-estimate the matrix completion model for hate crimes without Manchester and London. The results are virtually identical to those obtained from the full data.

Figure A-6 plots the difference between imputed and observed outcomes for each month using the full data (horizontal axis) against the difference when we omit Manchester and London. Each point is a month in the data. The 45-degree line is also plotted. All points fall very close to the 45-degree line, which indicates that the results are not being driven by Manchester and London.

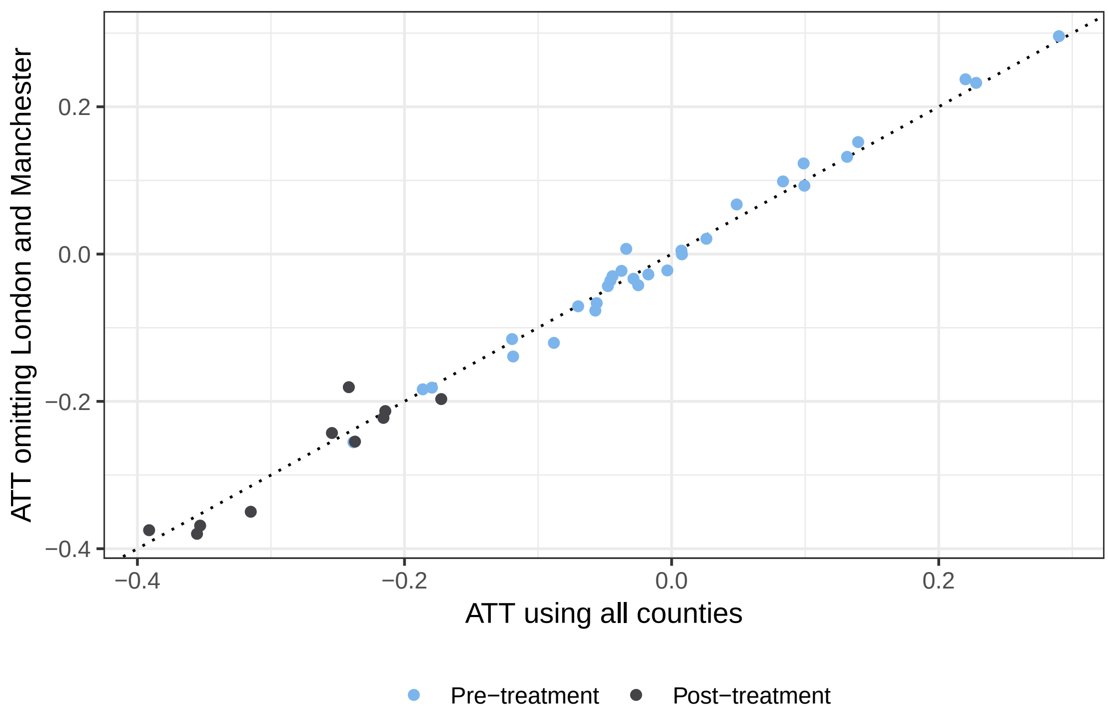


Figure A-6: Difference between observed and imputed outcomes for Merseyside using the full dataset (horizontal axis) and omitting Manchester and London (vertical axis). Each point is a month. The 45-degree line is shown.

D Twitter Data

D.1 Twitter Coding Instructions

The instructions provided to coders on Figure8 (formerly Crowdflower) were as follows:

Overview In this job, you will be presented with tweets about Muslims and Islam. Review the tweets to determine the sentiment so that we can have a greater understanding about the overall sentiment expressed by the author.

Steps

- Read the tweet.
- Determine if the tweet is relevant to Muslim people or Islam.
- Determine if the tweet expresses a positive, neutral, or negative attitude towards Muslims or Islam

Rules & Tips
The posts can be classified as positive, negative or neutral:

- **Positive tweets** portray Muslim people or Islam in a positive manner or argue that Muslims and Islam should not be portrayed negatively. For example, tweets that state that Muslims are not terrorists or extremists or that Islam is a peaceful religion or tweets that defend Muslims or Islam are positive.
- **Neutral tweets** are only informative in nature and provide no hint as to the mood of the author. They do not express an opinion about Muslims or Islam.
- **Negative tweets** are tweets in which some aspects of the tweet uncover a negative mood such as, criticism, insults or a negative comparison. These include tweets portraying Muslims as terrorists, extremists, or violent, and those making negative generalizations about Muslims or Islam as a whole.
- **Irrelevant tweets** do not mention Muslims or Islam or are not in English. These include tweets where the word “Muslim” or “Islam” appears in the handle of a Twitter user and tweets in foreign languages, for example.
- **Note:** Tweets that are purely factual (links to news articles without comment) are not necessarily Neutral — consider whether the fact/news itself is Positive or Negative regarding the business and select one of those when possible.

D.2 Twitter Data Descriptive Statistics

Table A-2: Proportion of Relevant and Anti-Muslim Tweets Pre and Post-Salah by Team

	type	team	post_salah	mean
1	Muslim Relevant / Total	everton	0	0.0010
2	Muslim Relevant / Total	everton	1	0.0016
3	Muslim Relevant / Total	liverpool	0	0.0027
4	Muslim Relevant / Total	liverpool	1	0.0046
5	Muslim Relevant / Total	other_big_teams	0	0.0026
6	Muslim Relevant / Total	other_big_teams	1	0.0040
7	Anti-Muslim / Total	everton	0	0.0002
8	Anti-Muslim / Total	everton	1	0.0003
9	Anti-Muslim / Total	liverpool	0	0.0002
10	Anti-Muslim / Total	liverpool	1	0.0004
11	Anti-Muslim / Total	other_big_teams	0	0.0002
12	Anti-Muslim / Total	other_big_teams	1	0.0004
13	Anti-Muslim / Muslim Relevant	everton	0	0.1780
14	Anti-Muslim / Muslim Relevant	everton	1	0.2237
15	Anti-Muslim / Muslim Relevant	liverpool	0	0.0715
16	Anti-Muslim / Muslim Relevant	liverpool	1	0.0757
17	Anti-Muslim / Muslim Relevant	other_big_teams	0	0.0703
18	Anti-Muslim / Muslim Relevant	other_big_teams	1	0.1037

D.3 Twitter Data Additional Data Analysis

As an alternative method of analyzing the effect of Salah joining Liverpool on the monthly proportion of anti-Muslim tweets produced by Liverpool fans, we conduct difference-in-differences estimation as follows:

$$y \;=\; \beta_0 + \beta_1 T + \beta_2 L + \beta_3 (T \cdot L) + \varepsilon \tag{A-2}$$

Here T is a dummy variable for the time period, equal to 1 in the post-Salah period and 0 in the pre-Salah period, and L is a dummy variable for Liverpool group membership, equal to 1 for Liverpool and 0 for other teams. The interacted term $(T \cdot L)$ is a dummy variable indicating when $L = T = 1$. If the coefficient β_3 on $(T \cdot L)$ is negative, as expected, then Liverpool fans tweet less anti-Muslim content in the post-Salah period relative to the pre-Salah period, compared to fans of other teams. We conduct this analysis comparing Liverpool fans' tweets to tweets produced by fans of other large teams as well as Everton F.C.. We use the proportion of anti-Muslim tweets (anti-Muslim tweets / tweets relevant to Islam or Muslims) as our outcome variable y.

Because there is only one treated unit and standard errors may be misleading, we again undertake an alternative form of inference, whereby we randomly assign a single unit to be treated, with treatment beginning in a randomly chosen month that is at least 4 months after the first observations in our dataset and as late as the actual treatment month. We then estimate the difference-in-difference model above. We repeat this procedure 10,000 times to generate a null distribution of the parameter estimate. We then compute a p-value by calculating the proportion of simulated coefficient estimates that are at least as small as the actual observed estimate.

The result of this exercise is presented in Figure A-7, which shows a histogram of the null distribution generated using the placebo approach described above. The vertical line shows the actual estimate of the model in equation A-2. The estimated one-sided p-value is 0.07. In other words, roughly 7% of simulations generated a point estimate less than -0.038. We interpret this to be suggestive evidence in favor of our Salah effect hypothesis.

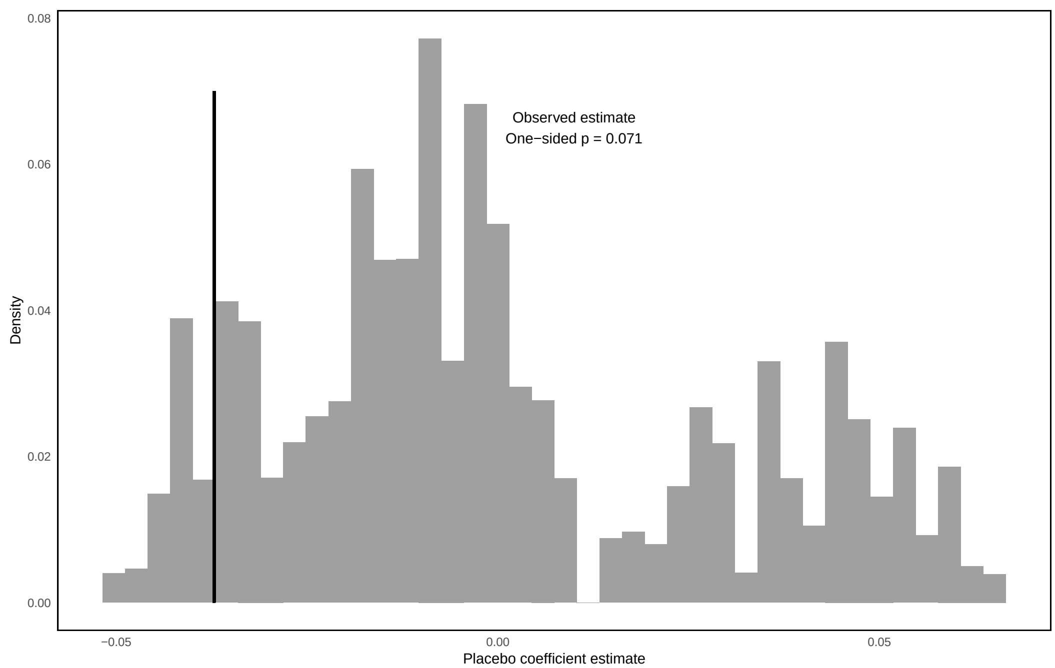


Figure A-7: The histogram shows the simulated null distribution of difference-in-differences estimates. The solid black line shows the observed coefficient for Liverpool. The one-sided p-value is 0.07.

E Survey Experiment

E.1 Vignette Descriptions

Respondents in the success condition then saw a picture of Mo Salah holding the Golden Boot with the following text:

> *In the 2017-18 season, Salah scored 43 goals for Liverpool, setting numerous club and league records along the way. For his efforts, he was named the Premier League's Player of the Month three times, won the Golden Boot, and was awarded the PFA Players' Player of the Year award. Along with Christiano Ronaldo and Luca Modric, he was shortlisted for UEFA Player of the Year. He recently won the FIFA Puskás award for best goal.*
>
> *Salah was also central in taking Egypt to the World Cup and Liverpool F.C. to the Champions League final.*

Respondents in the failure treatment saw an image of Salah looking regretful with the following text:

> *Despite a successful 2017-18 season, some believe he is underperforming this season. As of late October, he had scored only 4 goals in Premier League play.*[1] *Due to this lackluster performance, some critics have suggested that Salah will be a 'one-season wonder.'*

After the success/failure treatment, respondents then received a treatment emphasizing either Salah's character or his religiosity. Respondents who received the character treatment saw a picture of Salah with his daughter and the following text:

> *In addition to his goal-scoring, Salah is known for his character both on and off the pitch. In his native Egypt, Salah privately donated millions of pounds to charity and to a leading anti-drug campaign. Always a sportsman, Salah does not celebrate goals against his former teams and picked up only two yellow cards in 49 matches for Liverpool last season.*

Respondents in the religious treatment saw Salah prostrating with this text:

> *In addition to his goal scoring, Salah is known for an attachment to his Muslim identity both on and off the pitch. After every goal he scores, Salah touches his head to the ground in prayer. He also fasts during Ramadan (except on match days) and shares well wishes with his followers on social media during Islamic holidays. He named his daughter Makka after Islam's holiest site (Mecca).*

[1] This statistic was updated for respondents taking the survey in or after January 1, 2019 to read: "As of early January, he had scored in just 62% of Premier League games played — compared to 89% last season.

E.2 Balance Table for Survey Experiment

	Control (N=2887)	Char. - Fail. (N=1463)	Char. - Succ. (N=1454)	Rlgn. - Fail. (N=1421)	Rlgn - Succ. (N=1441)	F-Stat (p.value)
Age (Years)						0.89 (0.47)
N-Miss	136	161	170	204	173	
Mean (SD)	49.90 (12.84)	50.46 (12.22)	49.90 (12.71)	50.23 (12.43)	49.78 (11.44)	
Range	18.00 - 98.00	18.00 - 98.00	18.00 - 98.00	18.00 - 98.00	18.00 - 98.00	
Female						1.95 (0.1)
N-Miss	1	20	0	5	0	
Mean (SD)	0.28 (0.45)	0.27 (0.44)	0.25 (0.44)	0.25 (0.43)	0.28 (0.45)	
Range	0.00 - 1.00	0.00 - 1.00	0.00 - 1.00	0.00 - 1.00	0.00 - 1.00	
University Edu.						1.66 (0.16)
N-Miss	6	18	5	38	14	
Mean (SD)	0.32 (0.47)	0.34 (0.48)	0.31 (0.46)	0.33 (0.47)	0.31 (0.46)	
Range	0.00 - 1.00	0.00 - 1.00	0.00 - 1.00	0.00 - 1.00	0.00 - 1.00	
Salah Favorite						0.02 (1)
N-Miss	560	686	466	615	413	
Mean (SD)	0.52 (0.50)	0.52 (0.50)	0.52 (0.50)	0.53 (0.50)	0.52 (0.50)	
Range	0.00 - 1.00	0.00 - 1.00	0.00 - 1.00	0.00 - 1.00	0.00 - 1.00	
Karius Empathy						0.5 (0.73)
N-Miss	217	381	274	333	244	
Mean (SD)	0.38 (0.48)	0.36 (0.48)	0.38 (0.49)	0.39 (0.49)	0.38 (0.49)	
Range	0.00 - 1.00	0.00 - 1.00	0.00 - 1.00	0.00 - 1.00	0.00 - 1.00	
Liverpool Resident						0.75 (0.56)
N-Miss	0	0	0	0	0	
Mean (SD)	0.22 (0.42)	0.24 (0.43)	0.23 (0.42)	0.23 (0.42)	0.22 (0.41)	
Range	0.00 - 1.00	0.00 - 1.00	0.00 - 1.00	0.00 - 1.00	0.00 - 1.00	
Conservative						0.24 (0.91)
N-Miss	241	188	193	171	233	
Mean (SD)	0.27 (0.44)	0.27 (0.44)	0.28 (0.45)	0.28 (0.45)	0.28 (0.45)	
Range	0.00 - 1.00	0.00 - 1.00	0.00 - 1.00	0.00 - 1.00	0.00 - 1.00	

Table A-3: Summary statistics for several demographic variables as well as the outcome questions by treatment group. *Female* indicates proportion of respondents who identified as females. *University Edu.* indicates proportion of respondents who have at least some university education. *Salah Favorite* indicates the proportion of respondents who indicated that Salah is their favorite player. *Karius Empathy* indicates those who expressed empathy with Liverpool's goalkeeper Karius. *Liverpool Resident* indicates whether the respondents live in Liverpool. *Conservative* indicates respondents who indicated they are associated with the Conservative or UK Independence Party.

E.3 Additional Analysis

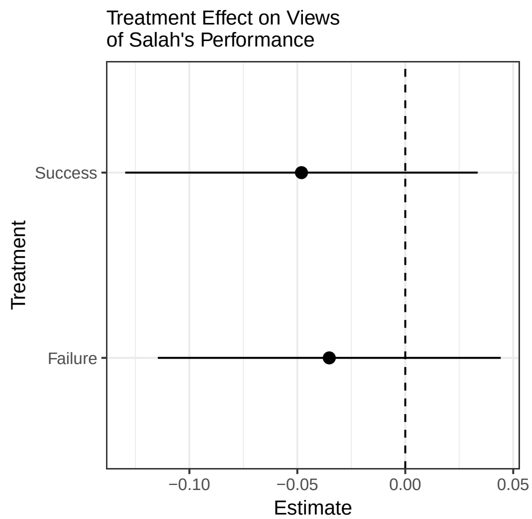


Figure A-8: Effects of treatments on views of Salah's performance

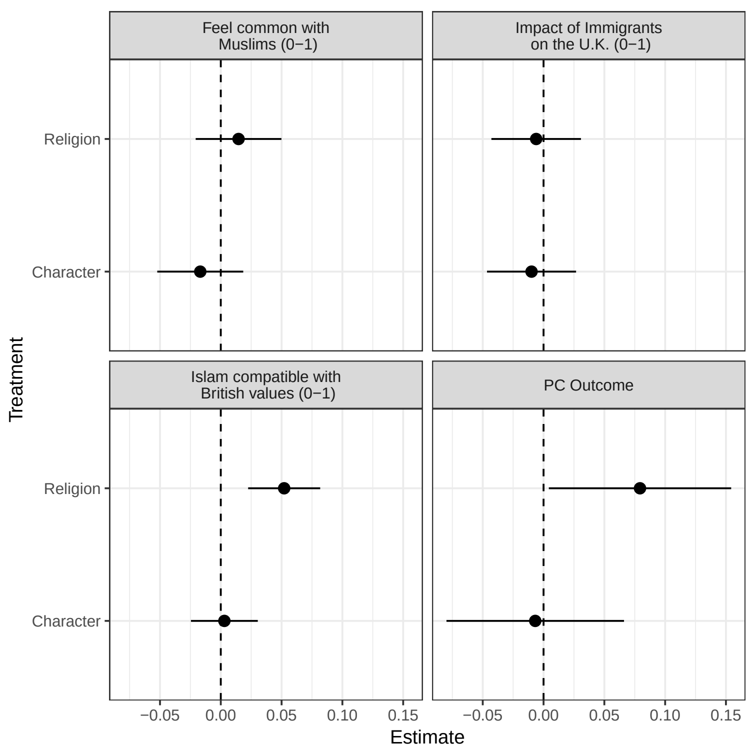


Figure A-9: Coef Plot for the average marginal component effects of the religion/character treatment

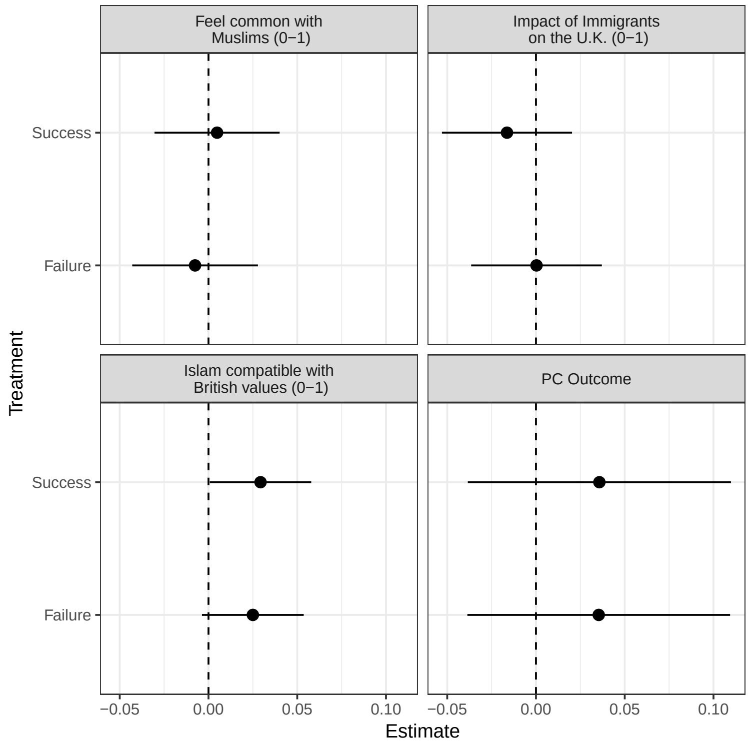


Figure A-10: Coef Plot for the average marginal component effects of the success/failure treatment

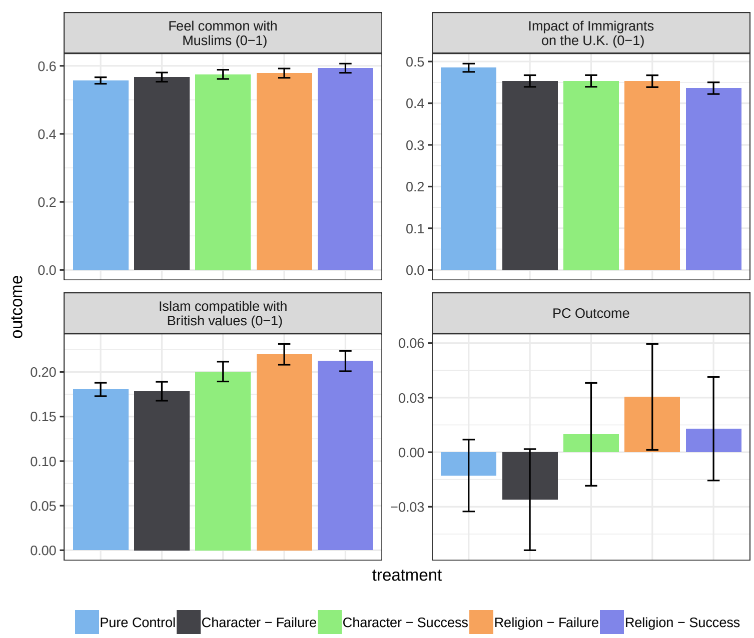


Figure A-11: Average of each outcome by treatment group

	PC Outcome	Muslims Common	Islam Compatible	Immigrant Impact
Constant	-0.02	0.57^{***}	0.18^{***}	0.46^{***}
	(0.03)	(0.01)	(0.01)	(0.01)
Character - Failure	-0.02	-0.02	-0.01	0.00
	(0.04)	(0.02)	(0.02)	(0.02)
Character - Success	0.00	-0.02	0.02	-0.02
	(0.05)	(0.02)	(0.02)	(0.02)
Religion - Failure	0.09	0.00	0.06^{**}	0.00
	(0.05)	(0.02)	(0.02)	(0.02)
Religion - Success	0.07	0.03	0.04^{*}	-0.01
	(0.05)	(0.02)	(0.02)	(0.02)
R^2	0.00	0.00	0.00	0.00
Adj. R^2	0.00	0.00	0.00	-0.00
Num. obs.	7515	8060	7771	7571
RMSE	2.25	1.11	0.90	1.12

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

Table A-4: Average treatment effects for the main outcomes.

	PC Outcome	Muslims Common	Islam Compatible	Immigrant Impact
(Intercept)	-0.02	0.57^{***}	0.18^{***}	0.47^{***}
	(0.03)	(0.01)	(0.01)	(0.01)
Character - Failure	-0.02	-0.02	-0.01	-0.01
	(0.04)	(0.02)	(0.02)	(0.02)
Character - Success	0.02	-0.01	0.02	-0.01
	(0.04)	(0.02)	(0.02)	(0.02)
Religion - Failure	0.09^{*}	0.01	0.06^{***}	0.00
	(0.04)	(0.02)	(0.02)	(0.02)
Religion - Success	0.08	0.03	0.05^{**}	-0.01
	(0.04)	(0.02)	(0.02)	(0.02)
Age	0.00	-0.00^{**}	0.00^{*}	0.00^{*}
	(0.00)	(0.00)	(0.00)	(0.00)
Female	0.06	0.06^{*}	-0.00	-0.00
	(0.06)	(0.03)	(0.02)	(0.03)
Univ. Edu.	0.68^{***}	0.24^{***}	0.22^{***}	0.25^{***}
	(0.06)	(0.03)	(0.03)	(0.03)
Character - Failure:Age	-0.00	-0.00	-0.00^{*}	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Character - Success:Age	-0.00	0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Religion - Failure:Age	0.00	0.00	0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Religion - Success:Age	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Character - Failure:Female	-0.01	-0.02	0.06	-0.05
	(0.10)	(0.05)	(0.04)	(0.05)
Character - Success:Female	0.02	0.00	-0.02	0.05
	(0.10)	(0.05)	(0.04)	(0.05)
Religion - Failure:Female	0.17	0.03	0.09^{*}	0.05
	(0.10)	(0.05)	(0.04)	(0.05)
Religion - Success:Female	0.01	-0.01	-0.01	0.03
	(0.10)	(0.05)	(0.04)	(0.05)
Character - Failure:Univ. Edu.	0.04	0.01	-0.05	0.09
	(0.09)	(0.04)	(0.04)	(0.05)
Character - Success:Univ. Edu.	0.02	-0.01	-0.03	0.09
	(0.10)	(0.04)	(0.04)	(0.05)
Religion - Failure:Univ. Edu.	-0.06	-0.05	-0.02	0.03
	(0.10)	(0.04)	(0.04)	(0.05)
Religion - Success:Univ. Edu.	-0.01	-0.01	-0.00	-0.01
	(0.10)	(0.04)	(0.04)	(0.05)
R^2	0.11	0.06	0.06	0.08
Adj. R^2	0.11	0.06	0.06	0.08
Num. obs.	7377	7914	7627	7429
RMSE	2.13	1.08	0.87	1.08

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

Table A-5: Lin regressions for the main outcomes.

	PC Outcome	Muslims Common	Islam Compatible	Immigrant Impact
(Intercept)	-0.02	0.58^{***}	0.17^{***}	0.47^{***}
	(0.04)	(0.02)	(0.02)	(0.02)
Character - Failure	-0.02	-0.01	-0.02	-0.00
	(0.06)	(0.03)	(0.02)	(0.03)
Character - Success	0.02	0.00	0.02	-0.03
	(0.07)	(0.03)	(0.03)	(0.03)
Religion - Failure	0.05	0.00	0.04	-0.01
	(0.07)	(0.03)	(0.03)	(0.03)
Religion - Success	0.11	0.05	0.06^{*}	-0.01
	(0.07)	(0.03)	(0.03)	(0.03)
Salah Fav.	0.01	-0.01	0.02	-0.00
	(0.06)	(0.03)	(0.02)	(0.03)
Character - Failure:Salah Fav.	-0.00	-0.02	0.01	0.00
	(0.09)	(0.05)	(0.03)	(0.05)
Character - Success:Salah Fav.	-0.04	-0.04	-0.02	0.02
	(0.09)	(0.04)	(0.04)	(0.05)
Religion - Failure:Salah Fav.	0.07	0.01	0.04	0.02
	(0.10)	(0.04)	(0.04)	(0.05)
Religion - Success:Salah Fav.	-0.06	-0.04	-0.03	0.01
	(0.09)	(0.04)	(0.04)	(0.05)
R^2	0.00	0.00	0.01	0.00
Adj. R^2	0.00	0.00	0.00	-0.00
Num. obs.	7025	7531	7265	7079
RMSE	2.26	1.11	0.90	1.12

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

Table A-6: Interacting the treatments with selecting Salah as the favorite player.

	PC Outcome	Muslims Common	Islam Compatible	Immigrant Impact
(Intercept)	0.08^{*}	0.61^{***}	0.21^{***}	0.51^{***}
	(0.03)	(0.02)	(0.01)	(0.02)
Character - Failure	-0.05	-0.04	-0.02	-0.01
	(0.05)	(0.03)	(0.02)	(0.03)
Character - Success	0.01	-0.02	0.01	-0.01
	(0.05)	(0.03)	(0.02)	(0.03)
Religion - Failure	0.10	0.02	0.06^{*}	-0.00
	(0.06)	(0.03)	(0.02)	(0.03)
Religion - Success	0.07	0.03	0.04	-0.01
	(0.06)	(0.03)	(0.02)	(0.03)
Conservative	-0.38^{***}	-0.14^{***}	-0.12^{***}	-0.15^{***}
	(0.06)	(0.03)	(0.02)	(0.03)
Character - Failure:Conservative	0.12	0.08	0.02	0.03
	(0.09)	(0.05)	(0.03)	(0.05)
Character - Success:Conservative	-0.01	0.00	0.02	-0.01
	(0.09)	(0.05)	(0.03)	(0.05)
Religion - Failure:Conservative	-0.03	-0.05	0.01	0.01
	(0.10)	(0.05)	(0.04)	(0.05)
Religion - Success:Conservative	-0.03	-0.00	-0.02	-0.01
	(0.09)	(0.05)	(0.03)	(0.05)
R^2	0.03	0.02	0.02	0.02
Adj. R^2	0.03	0.02	0.02	0.02
Num. obs.	7372	7900	7617	7417
RMSE	2.22	1.10	0.89	1.11

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

Table A-7: Interacting the treatments with an indicator for conservative views. This indicator is coded as 1 if the respondent identifies with the Conservative Party or the UK Independence Party. It is coded as 0 if the respondent identifies with the Labour Party, Liberal Democrats, other parties, or none of these parties.

	PC Outcome	Muslims Common	Islam Compatible	Immigrant Impact
(Intercept)	-0.06	0.57^{***}	0.17^{***}	0.45^{***}
	(0.03)	(0.02)	(0.01)	(0.02)
Character - Failure	-0.04	-0.03	-0.01	-0.01
	(0.05)	(0.02)	(0.02)	(0.03)
Character - Success	0.01	-0.01	0.02	-0.02
	(0.05)	(0.02)	(0.02)	(0.03)
Religion - Failure	0.05	-0.01	0.06^{**}	-0.02
	(0.05)	(0.02)	(0.02)	(0.03)
Religion - Success	0.04	0.02	0.03	-0.02
	(0.05)	(0.02)	(0.02)	(0.03)
Liverpool Res.	0.15^{*}	0.02	0.06^{*}	0.07^{*}
	(0.07)	(0.03)	(0.03)	(0.03)
Character - Failure:Liverpool Res.	0.08	0.06	-0.01	0.04
	(0.11)	(0.05)	(0.04)	(0.05)
Character - Success:Liverpool Res.	-0.03	-0.01	-0.02	-0.01
	(0.11)	(0.05)	(0.04)	(0.05)
Religion - Failure:Liverpool Res.	0.15	0.07	0.01	0.08
	(0.11)	(0.05)	(0.05)	(0.05)
Religion - Success:Liverpool Res.	0.13	0.01	0.04	0.04
	(0.12)	(0.05)	(0.05)	(0.06)
R^2	0.01	0.00	0.01	0.01
Adj. R^2	0.01	0.00	0.01	0.01
Num. obs.	7515	8060	7771	7571
RMSE	2.25	1.11	0.89	1.12

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

Table A-8: Interacting the treatments with an indicator for residing in Liverpool.

	PC Outcome	Muslims Common	Islam Compatible	Immigrant Impact
(Intercept)	-0.02	0.56^{***}	0.18^{***}	0.48^{***}
	(0.07)	(0.03)	(0.03)	(0.03)
Character - Failure	-0.11	-0.06	-0.02	-0.05
	(0.11)	(0.06)	(0.04)	(0.06)
Character - Success	-0.13	-0.04	-0.04	-0.07
	(0.11)	(0.05)	(0.04)	(0.05)
Religion - Failure	0.19	0.04	0.09	0.01
	(0.12)	(0.05)	(0.05)	(0.06)
Religion - Success	0.09	0.01	0.06	0.02
	(0.12)	(0.06)	(0.05)	(0.06)
Follow Liverpool	-0.00	0.02	-0.00	-0.02
	(0.07)	(0.04)	(0.03)	(0.04)
Character - Failure:Follow Liverpool	0.11	0.05	0.02	0.06
	(0.12)	(0.06)	(0.04)	(0.06)
Character - Success:Follow Liverpool	0.15	0.03	0.06	0.06
	(0.12)	(0.06)	(0.04)	(0.06)
Religion - Failure:Follow Liverpool	-0.12	-0.04	-0.04	-0.02
	(0.13)	(0.06)	(0.05)	(0.06)
Religion - Success:Follow Liverpool	-0.02	0.02	-0.02	-0.04
	(0.13)	(0.06)	(0.05)	(0.06)
R^2	0.00	0.00	0.01	0.00
Adj. R^2	0.00	0.00	0.00	-0.00
Num. obs.	7513	8057	7768	7569
RMSE	2.25	1.11	0.90	1.12

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

Table A-9: Interacting the treatments with an indicator for closely following Liverpool FC. People who follow Liverpool very closely (watch every match, read news almost daily) are coded as 1 and people who follow Liverpool less often are coded as 0.

	PC Outcome	Muslims Common	Islam Compatible	Immigrant Impact
(Intercept)	-0.02	0.57^{***}	0.18^{***}	0.47^{***}
	(0.03)	(0.01)	(0.01)	(0.01)
Character	-0.00	-0.01	0.00	-0.01
	(0.04)	(0.02)	(0.01)	(0.02)
Religion	0.08^{*}	0.02	0.05^{***}	-0.00
	(0.04)	(0.02)	(0.01)	(0.02)
Age	0.00	-0.00^{**}	0.00^{*}	0.00^{*}
	(0.00)	(0.00)	(0.00)	(0.00)
Female	0.06	0.06^{*}	-0.00	-0.00
	(0.06)	(0.03)	(0.02)	(0.03)
Univ. Edu.	0.68^{***}	0.24^{***}	0.22^{***}	0.25^{***}
	(0.06)	(0.03)	(0.03)	(0.03)
Character:Age	-0.00	0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Religion:Age	-0.00	0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Character:Female	0.01	-0.01	0.02	-0.00
	(0.08)	(0.04)	(0.03)	(0.04)
Religion:Female	0.08	0.01	0.03	0.04
	(0.08)	(0.04)	(0.03)	(0.04)
Character:Univ. Edu.	0.03	0.00	-0.04	0.08^{*}
	(0.08)	(0.04)	(0.03)	(0.04)
Religion:Univ. Edu.	-0.03	-0.03	-0.01	0.01
	(0.08)	(0.04)	(0.04)	(0.04)
R^2	0.11	0.06	0.06	0.08
Adj. R^2	0.11	0.06	0.06	0.08
Num. obs.	7377	7914	7627	7429
RMSE	2.13	1.08	0.87	1.08

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

Table A-10: Lin regressions using the character/religion treatments.

	PC Outcome	Muslims Common	Islam Compatible	Immigrant Impact
(Intercept)	0.08^{*}	0.61^{***}	0.21^{***}	0.51^{***}
	(0.03)	(0.02)	(0.01)	(0.02)
Character	-0.02	-0.03	-0.00	-0.01
	(0.05)	(0.02)	(0.02)	(0.02)
Religion	0.09	0.02	0.05^{**}	-0.01
	(0.05)	(0.02)	(0.02)	(0.02)
Conservative	-0.38^{***}	-0.14^{***}	-0.12^{***}	-0.15^{***}
	(0.06)	(0.03)	(0.02)	(0.03)
Character:Conservative	0.06	0.04	0.02	0.01
	(0.08)	(0.04)	(0.03)	(0.04)
Religion:Conservative	-0.03	-0.03	-0.00	0.00
	(0.08)	(0.04)	(0.03)	(0.04)
R^2	0.03	0.02	0.02	0.02
Adj. R^2	0.03	0.02	0.02	0.02
Num. obs.	7372	7900	7617	7417
RMSE	2.22	1.10	0.89	1.11

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

Table A-11: Interacting the character/religion treatments with an indicator for conservative views. This indicator is coded as 1 if the respondent identifies with the Conservative Party or the UK Independence Party. It is coded as 0 if the respondent identifies with the Labour Party, Liberal Democrats, other parties, or none of these parties.

	PC Outcome	Muslims Common	Islam Compatible	Immigrant Impact
(Intercept)	-0.02	0.57^{***}	0.18^{***}	0.47^{***}
	(0.03)	(0.01)	(0.01)	(0.01)
Failure	0.03	-0.00	0.02	-0.00
	(0.04)	(0.02)	(0.01)	(0.02)
Success	0.05	0.01	0.03^{*}	-0.01
	(0.04)	(0.02)	(0.01)	(0.02)
Age	0.00	-0.00^{**}	0.00^{*}	0.00^{*}
	(0.00)	(0.00)	(0.00)	(0.00)
Female	0.06	0.06^{*}	-0.00	-0.00
	(0.06)	(0.03)	(0.02)	(0.03)
Univ. Edu.	0.68^{***}	0.24^{***}	0.22^{***}	0.25^{***}
	(0.06)	(0.03)	(0.03)	(0.03)
Failure:Age	-0.00	0.00	-0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Success:Age	-0.00	0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Failure:Female	0.07	0.01	0.07^{*}	-0.00
	(0.08)	(0.04)	(0.03)	(0.04)
Success:Female	0.02	-0.00	-0.02	0.04
	(0.08)	(0.04)	(0.03)	(0.04)
Failure:Univ. Edu.	-0.02	-0.02	-0.04	0.06
	(0.08)	(0.04)	(0.03)	(0.04)
Success:Univ. Edu.	0.01	-0.01	-0.02	0.04
	(0.08)	(0.04)	(0.03)	(0.04)
R^2	0.11	0.06	0.06	0.08
Adj. R^2	0.10	0.06	0.06	0.08
Num. obs.	7377	7914	7627	7429
RMSE	2.13	1.08	0.87	1.08

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

Table A-12: Lin regressions using the success/failure treatments.

	PC Outcome	Muslims Common	Islam Compatible	Immigrant Impact
(Intercept)	0.08^{*}	0.61^{***}	0.21^{***}	0.51^{***}
	(0.03)	(0.02)	(0.01)	(0.02)
Failure	0.02	−0.01	0.02	−0.01
	(0.05)	(0.02)	(0.02)	(0.02)
Success	0.04	0.01	0.03	−0.01
	(0.05)	(0.02)	(0.02)	(0.02)
Conservative	-0.38^{***}	-0.14^{***}	-0.12^{***}	-0.15^{***}
	(0.06)	(0.03)	(0.02)	(0.03)
Failure:Conservative	0.05	0.01	0.02	0.02
	(0.08)	(0.04)	(0.03)	(0.04)
Success:Conservative	−0.02	0.00	0.00	−0.01
	(0.08)	(0.04)	(0.03)	(0.04)
R^2	0.03	0.02	0.02	0.02
Adj. R^2	0.03	0.01	0.01	0.02
Num. obs.	7372	7900	7617	7417
RMSE	2.22	1.10	0.89	1.11

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

Table A-13: Interacting the success/failure treatments with an indicator for conservative views. This indicator is coded as 1 if the respondent identifies with the Conservative Party or the UK Independence Party. It is coded as 0 if the respondent identifies with the Labour Party, Liberal Democrats, other parties, or none of these parties.

	PC Outcome	Muslims Common	Islam Compatible	Immigrant Impact
Constant	−0.02	0.57^{***}	0.18^{***}	0.46^{***}
	(0.03)	(0.01)	(0.01)	(0.01)
Failure	0.04	−0.01	0.02	0.00
	(0.04)	(0.02)	(0.01)	(0.02)
Success	0.04	0.00	0.03^{*}	−0.02
	(0.04)	(0.02)	(0.01)	(0.02)
R^2	0.00	0.00	0.00	0.00
Adj. R^2	-0.00	-0.00	0.00	0.00
Num. obs.	7515	8060	7771	7571
RMSE	2.26	1.11	0.90	1.12

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

Table A-14: Main regressions using the success/failure treatments.

	PC Outcome	Muslims Common	Islam Compatible	Immigrant Impact
(Intercept)	-0.02	0.58^{***}	0.17^{***}	0.47^{***}
	(0.04)	(0.02)	(0.02)	(0.02)
Failure	0.02	-0.01	0.01	-0.00
	(0.06)	(0.03)	(0.02)	(0.03)
Success	0.07	0.03	0.04	-0.02
	(0.06)	(0.03)	(0.02)	(0.03)
Salah Fav.	0.01	-0.01	0.02	-0.00
	(0.06)	(0.03)	(0.02)	(0.03)
Failure:Salah Fav.	0.04	-0.01	0.02	0.01
	(0.08)	(0.04)	(0.03)	(0.04)
Success:Salah Fav.	-0.05	-0.04	-0.02	0.01
	(0.08)	(0.04)	(0.03)	(0.04)
R^2	0.00	0.00	0.00	0.00
Adj. R^2	-0.00	0.00	0.00	-0.00
Num. obs.	7025	7531	7265	7079
RMSE	2.26	1.11	0.90	1.12

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

Table A-15: Interacting the success/failure treatments with selecting Salah as the favorite player.

	PC Outcome	Muslims Common	Islam Compatible	Immigrant Impact
(Intercept)	-0.06	0.57^{***}	0.17^{***}	0.45^{***}
	(0.03)	(0.02)	(0.01)	(0.02)
Failure	0.01	-0.02	0.02	-0.01
	(0.04)	(0.02)	(0.02)	(0.02)
Success	0.03	0.01	0.03	-0.02
	(0.04)	(0.02)	(0.02)	(0.02)
Liverpool Res.	0.15^{*}	0.02	0.06^{*}	0.07^{*}
	(0.07)	(0.03)	(0.03)	(0.03)
Failure:Liverpool Res.	0.11	0.07	0.00	0.06
	(0.09)	(0.04)	(0.04)	(0.04)
Success:Liverpool Res.	0.04	-0.00	0.01	0.02
	(0.09)	(0.04)	(0.04)	(0.05)
R^2	0.01	0.00	0.01	0.01
Adj. R^2	0.01	0.00	0.00	0.01
Num. obs.	7515	8060	7771	7571
RMSE	2.25	1.11	0.90	1.12

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

Table A-16: Interacting the success/failure treatments with an indicator for residing in Liverpool.

	PC Outcome	Muslims Common	Islam Compatible	Immigrant Impact
(Intercept)	-0.02	0.56^{***}	0.18^{***}	0.48^{***}
	(0.07)	(0.03)	(0.03)	(0.03)
Failure	0.04	-0.01	0.03	-0.02
	(0.10)	(0.05)	(0.04)	(0.05)
Success	-0.02	-0.01	0.01	-0.03
	(0.10)	(0.04)	(0.04)	(0.05)
Follow Liverpool	-0.00	0.02	-0.00	-0.02
	(0.07)	(0.04)	(0.03)	(0.04)
Failure:Follow Liverpool	-0.00	0.01	-0.01	0.02
	(0.11)	(0.05)	(0.04)	(0.05)
Success:Follow Liverpool	0.06	0.02	0.02	0.01
	(0.10)	(0.05)	(0.04)	(0.05)
R^2	0.00	0.00	0.00	0.00
Adj. R^2	-0.00	0.00	0.00	-0.00
Num. obs.	7513	8057	7768	7569
RMSE	2.26	1.11	0.90	1.12

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

Table A-17: Interacting the success/failure treatments with an indicator for closely following Liverpool FC. People who follow Liverpool very closely (watch every match, read news almost daily) are coded as 1 and people who follow Liverpool less often are coded as 0.

	PC Outcome	Muslims Common	Islam Compatible	Immigrant Impact
Constant	-0.02	0.57^{***}	0.18^{***}	0.46^{***}
	(0.03)	(0.01)	(0.01)	(0.01)
Character	-0.01	-0.02	0.00	-0.01
	(0.04)	(0.02)	(0.01)	(0.02)
Religion	0.08^{*}	0.01	0.05^{***}	-0.01
	(0.04)	(0.02)	(0.02)	(0.02)
R^2	0.00	0.00	0.00	0.00
Adj. R^2	0.00	0.00	0.00	-0.00
Num. obs.	7515	8060	7771	7571
RMSE	2.25	1.11	0.90	1.12

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

Table A-18: Main regressions using the character/religion treatments.

	PC Outcome	Muslims Common	Islam Compatible	Immigrant Impact
(Intercept)	-0.02	0.58^{***}	0.17^{***}	0.47^{***}
	(0.04)	(0.02)	(0.02)	(0.02)
Character	-0.00	-0.00	0.00	-0.02
	(0.06)	(0.03)	(0.02)	(0.03)
Religion	0.08	0.03	0.05^{*}	-0.01
	(0.06)	(0.03)	(0.02)	(0.03)
Salah Fav.	0.01	-0.01	0.02	-0.00
	(0.06)	(0.03)	(0.02)	(0.03)
Character:Salah Fav.	-0.02	-0.03	-0.00	0.01
	(0.08)	(0.04)	(0.03)	(0.04)
Religion:Salah Fav.	0.01	-0.02	0.00	0.02
	(0.08)	(0.04)	(0.03)	(0.04)
R^2	0.00	0.00	0.00	0.00
Adj. R^2	0.00	0.00	0.00	-0.00
Num. obs.	7025	7531	7265	7079
RMSE	2.26	1.11	0.90	1.12

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

Table A-19: Interacting the character/religion treatments with selecting Salah as the favorite player.

	PC Outcome	Muslims Common	Islam Compatible	Immigrant Impact
(Intercept)	-0.06	0.57^{***}	0.17^{***}	0.45^{***}
	(0.03)	(0.02)	(0.01)	(0.02)
Character	-0.01	-0.02	0.01	-0.01
	(0.04)	(0.02)	(0.02)	(0.02)
Religion	0.05	0.01	0.05^{**}	-0.02
	(0.04)	(0.02)	(0.02)	(0.02)
Liverpool Res.	0.15^{*}	0.02	0.06^{*}	0.07^{*}
	(0.07)	(0.03)	(0.03)	(0.03)
Character:Liverpool Res.	0.03	0.02	-0.02	0.02
	(0.09)	(0.04)	(0.04)	(0.04)
Religion:Liverpool Res.	0.14	0.04	0.03	0.06
	(0.10)	(0.04)	(0.04)	(0.05)
R^2	0.01	0.00	0.01	0.01
Adj. R^2	0.01	0.00	0.01	0.01
Num. obs.	7515	8060	7771	7571
RMSE	2.25	1.11	0.89	1.12

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

Table A-20: Interacting the character/religion treatments with an indicator for residing in Liverpool.

	PC Outcome	Muslims Common	Islam Compatible	Immigrant Impact
(Intercept)	-0.02	0.56^{***}	0.18^{***}	0.48^{***}
	(0.07)	(0.03)	(0.03)	(0.03)
Character	-0.12	-0.05	-0.03	-0.06
	(0.09)	(0.05)	(0.03)	(0.05)
Religion	0.14	0.02	0.07	0.02
	(0.10)	(0.05)	(0.04)	(0.05)
Follow Liverpool	-0.00	0.02	-0.00	-0.02
	(0.07)	(0.04)	(0.03)	(0.04)
Character:Follow Liverpool	0.13	0.04	0.04	0.06
	(0.10)	(0.05)	(0.04)	(0.05)
Religion:Follow Liverpool	-0.07	-0.01	-0.03	-0.03
	(0.11)	(0.05)	(0.04)	(0.05)
R^2	0.00	0.00	0.00	0.00
Adj. R^2	0.00	0.00	0.00	0.00
Num. obs.	7513	8057	7768	7569
RMSE	2.25	1.11	0.90	1.12

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

Table A-21: Interacting the character/religion treatments with an indicator for closely following Liverpool FC. People who follow Liverpool very closely (watch every match, read news almost daily) are coded as 1 and people who follow Liverpool less often are coded as 0.

	PC Outcome	Muslims Common	Islam Compatible	Immigrant Impact
(Intercept)	-0.03	0.56^{***}	0.18^{***}	0.47^{***}
	(0.04)	(0.02)	(0.01)	(0.02)
Character - Failure	-0.08	-0.03	-0.03	-0.03
	(0.06)	(0.03)	(0.02)	(0.03)
Character - Success	-0.04	-0.03	-0.00	-0.03
	(0.06)	(0.03)	(0.02)	(0.03)
Religion - Failure	0.05	-0.01	0.04	-0.02
	(0.06)	(0.03)	(0.02)	(0.03)
Religion - Success	0.06	0.03	0.04	-0.02
	(0.06)	(0.03)	(0.02)	(0.03)
Karius Empathy	0.01	0.04	-0.01	-0.02
	(0.06)	(0.03)	(0.02)	(0.03)
Character - Failure:Karius Empathy	0.17	0.05	0.05	0.08
	(0.09)	(0.05)	(0.03)	(0.05)
Character - Success:Karius Empathy	0.12	0.04	0.04	0.04
	(0.09)	(0.04)	(0.04)	(0.05)
Religion - Failure:Karius Empathy	0.11	0.03	0.05	0.05
	(0.10)	(0.05)	(0.04)	(0.05)
Religion - Success:Karius Empathy	0.03	-0.01	0.02	0.03
	(0.10)	(0.04)	(0.04)	(0.05)
R^2	0.01	0.01	0.01	0.00
Adj. R^2	0.00	0.00	0.00	0.00
Num. obs.	7510	8040	7758	7563
RMSE	2.25	1.11	0.90	1.12

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

Table A-22: Interacting the treatments with expressing sympathy with Karius. Respondents are coded as empathetic with Karius if they did not agree with the criticism that Karius received after following the 2018 Champions League final.

	PC Outcome	Muslims Common	Islam Compatible	Immigrant Impact
(Intercept)	-0.03	0.56^{***}	0.18^{***}	0.47^{***}
	(0.04)	(0.02)	(0.01)	(0.02)
Character	-0.06	-0.03	-0.02	-0.03
	(0.05)	(0.02)	(0.02)	(0.02)
Religion	0.05	0.01	0.04^{*}	-0.02
	(0.05)	(0.02)	(0.02)	(0.02)
Karius Empathy	0.01	0.04	-0.01	-0.02
	(0.06)	(0.03)	(0.02)	(0.03)
Character:Karius Empathy	0.15	0.05	0.05	0.06
	(0.08)	(0.04)	(0.03)	(0.04)
Religion:Karius Empathy	0.07	0.01	0.03	0.04
	(0.08)	(0.04)	(0.03)	(0.04)
R^2	0.00	0.00	0.00	0.00
Adj. R^2	0.00	0.00	0.00	0.00
Num. obs.	7510	8040	7758	7563
RMSE	2.25	1.11	0.90	1.12

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

Table A-23: Interacting the character/religion treatments with an indicator for empathy with Karius. Respondents are coded as empathetic with Karius if they did not agree with the criticism that Karius received after following the 2018 Champions League final.

	PC Outcome	Muslims Common	Islam Compatible	Immigrant Impact
(Intercept)	-0.03	0.56^{***}	0.18^{***}	0.47^{***}
	(0.04)	(0.02)	(0.01)	(0.02)
Character	-0.06	-0.03	-0.02	-0.03
	(0.05)	(0.02)	(0.02)	(0.02)
Religion	0.05	0.01	0.04^{*}	-0.02
	(0.05)	(0.02)	(0.02)	(0.02)
Karius Empathy	0.01	0.04	-0.01	-0.02
	(0.06)	(0.03)	(0.02)	(0.03)
Character:Karius Empathy	0.15	0.05	0.05	0.06
	(0.08)	(0.04)	(0.03)	(0.04)
Religion:Karius Empathy	0.07	0.01	0.03	0.04
	(0.08)	(0.04)	(0.03)	(0.04)
R^2	0.00	0.00	0.00	0.00
Adj. R^2	0.00	0.00	0.00	0.00
Num. obs.	7510	8040	7758	7563
RMSE	2.25	1.11	0.90	1.12

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

Table A-24: Interacting the success/failure treatments with an indicator for empathy with Karius. Respondents are coded as empathetic with Karius if they did not agree with the criticism that Karius received after following the 2018 Champions League final.

	PC Outcome	Muslims Common	Islam Compatible	Immigrant Impact
Constant	-0.00	0.56^{***}	0.20^{***}	0.47^{***}
	(0.03)	(0.02)	(0.01)	(0.02)
Day After Victory	-0.01	-0.00	0.01	-0.01
	(0.05)	(0.02)	(0.02)	(0.02)
R^2	0.00	0.00	0.00	0.00
Adj. R^2	-0.00	-0.00	-0.00	-0.00
Num. obs.	3022	3243	3113	3037
RMSE	2.27	1.12	0.90	1.12

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

Table A-25: Relationship between victory and outcomes. This compares responses on the day after a Liverpool victory with responses on the day before a Liverpool victory).

	PC Outcome	Muslims Common	Islam Compatible	Immigrant Impact
Constant	0.01	0.57^{***}	0.20^{***}	0.46^{***}
	(0.02)	(0.01)	(0.01)	(0.01)
Day After Victory	-0.02	-0.02	0.01	-0.00
	(0.04)	(0.02)	(0.02)	(0.02)
R^2	0.00	0.00	0.00	0.00
Adj. R^2	-0.00	0.00	-0.00	-0.00
Num. obs.	7515	8060	7771	7571
RMSE	2.26	1.11	0.90	1.12

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

Table A-26: Relationship between victory and outcomes. This compares responses on the day after a Liverpool victory with responses on all other days.

	PC Outcome	Muslims Common	Islam Compatible	Immigrant Impact
Constant	-0.02	0.56^{***}	0.19^{***}	0.46^{***}
	(0.03)	(0.02)	(0.01)	(0.02)
Day After Salah Scores	0.01	0.01	0.02	-0.00
	(0.05)	(0.02)	(0.02)	(0.03)
R^2	0.00	0.00	0.00	0.00
Adj. R^2	-0.00	-0.00	0.00	-0.00
Num. obs.	2587	2774	2665	2602
RMSE	2.26	1.11	0.89	1.12

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

Table A-27: Relationship between victory and outcomes. This compares responses on the day after Salah scored with responses on the day before Salah scored.

	PC Outcome	Muslims Common	Islam Compatible	Immigrant Impact
Constant	-0.01	0.56^{***}	0.20^{***}	0.46^{***}
	(0.03)	(0.02)	(0.01)	(0.02)
Day After Salah Scores	0.00	0.00	0.01	-0.00
	(0.05)	(0.02)	(0.02)	(0.02)
R^2	0.00	0.00	0.00	0.00
Adj. R^2	-0.00	-0.00	-0.00	-0.00
Num. obs.	3080	3303	3171	3095
RMSE	2.26	1.12	0.90	1.12

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

Table A-28: Relationship between victory and outcomes. This compares responses on the day after Salah scored with responses on all other days.