Who Should Get Vaccinated First?

Welfare Chauvinism Against Universal Preventive Healthcare During the COVID-19 Pandemic[*]

Merlin Schaeffer[a] and Mikkel Haderup Larsen[b]

Abstract

Only a universal vaccination program, which immunizes the population irrespective of origin and ethnicity – similar to the spread of the Coronavirus itself – will effectively fight the public health threat posed by COVID-19. This qualifies the COVID-19 vaccination program as an interesting case to test for welfare chauvinism. On that premise, we conducted a pre-registered paired-vignette experiment during the first week of the Danish vaccination program, trying to find out whether recent immigrants and Muslim minorities are regarded as less deserving of access to critical preventive healthcare amid a pandemic. Our results show that Muslim and immigrant diabetes patients are indeed systematically seen as less deserving of an early vaccination. These results are consistent even if we focus on patients who followed the guidelines on facemask wearing and social distancing and who have diabetes despite their responsibly healthy lifestyle. Contra our pre-registered hypotheses, we find only weak evidence that immigrants or Muslims are penalized more harshly for not having followed these guidelines, or for having diabetes because of an unhealthy lifestyle. Compared with previous research, we exploit a timely and significant event to study welfare chauvinism and are the first to disentangle minority status from stereotypes about their anti-social freeriding behavior and irresponsible lifestyles.

[a] Corresponding author, Department of Sociology, University of Copenhagen & WZB Berlin Social Science Center.
[b] Department of Sociology, University of Copenhagen.

Introduction

Social science research on welfare chauvinism shows that considerable shares of native-born citizens would like to treat immigrants and their descendants as second-class citizens with no or limited access to welfare state benefits (Kulin, Eger, and Hjerm 2016; van Oorschot 2008a). Larsen and Schaeffer (2020) provide first evidence of healthcare chauvinism during the COVID-19 pandemic and claim that their work overcomes a potential shortfall of previous research on welfare chauvinistic attitudes: While policy makers frequently justify reforms that limit access to welfare benefits for immigrants as measures that incentivize fast labor market integration and assimilation into the mainstream, similar arguments cannot be made with respect to non-treatment of a COVID-19 infection.

The COVID-19 pandemic may serve as informative test case to study the profoundness of welfare chauvinistic attitudes for yet another reason. Generally, people distinguish healthcare from other welfare services and frequently regard it as a basic human need – especially in countries with a national healthcare system (Laenen, Rossetti, and van Oorschot 2019). Jensen and Petersen explain this with "the particular nature of health problems over human evolutionary history involving primarily random infections and injuries" (2017:69), and provide extensive experimental evidence that this deep-wired support for healthcare may even override other factors that usually shape judgements about welfare deservingness. COVID-19 is the most recent in a long history of infectious diseases that spread among humans regardless of their status, wealth and merit – or origin and ethnicity. In consequence, *preventive* public health responses to the pandemic – such as access to a public vaccination program – should be as universal as the human susceptibility to a COVID-19 infection. Against this background, the case of equal access to preventive healthcare during a pandemic, frames the expression of welfare chauvinism as a particularly deep-sitting and profound public opinion.

On that theoretical premise, we conducted a pre-registered conjoint online survey experiment among a random probability sample of 2,500 native-born Danes, trying to find out whether recent immigrants and Muslim minorities are regarded as less deserving of critical access to preventive healthcare amid a pandemic. Respondents were presented with two paired-vignettes – both describing a diabetes patient facing

a high risk of severe illness from COVID-19 – and asked to choose who of the two should get vaccinated as part of the groups initially prioritized in the vaccination program.

Beyond exploiting a timely event, our experimental design is furthermore the first to explicitly disentangle minority status – especially Muslim minority status – from stereotypes about their anti-social behavior and irresponsible lifestyles. This allows us to study pure apathy against Muslims and immigrants irrespective of malleable beliefs about their stereotypical behavior, but also whether they face extra penalties for showing such behaviors. Using a full factorial design, our paired vignettes randomized whether the diabetes patient was born in Denmark or immigrated within the past year and whether he had a Danish/Nordic or a Muslim name. Making sure to map all dimensions of the deservingness heuristic (see theory section), we further randomized whether the described person followed the government guidelines on social distancing and facemask wearing (antisocial behavior), and whether he has diabetes despite a healthy or because of an unhealthy lifestyle (irresponsible lifestyle).

Theoretical background

Welfare chauvinism describes the aversion of non-immigrant-origin citizens to share the benefits of a welfare state with immigrants and their descendants. Andersen and Bjørklund originated the term and put it bluntly: welfare chauvinists claim that "welfare services should be restricted to 'our own'" (Andersen and Bjørklund 1990:212). Defined such, welfare chauvinism is an alternative to Alesina and Glaeser's (2004) warning that – especially European – countries will face difficulties in maintaining welfare systems alongside continuing immigration because of the majority population's unwillingness to share welfare benefits with immigrants and their descendants. Alesina and Glaeser's hypothesis is informed by the example of the US, where racism and the stereotype that Black or Hispanic Americans would over-proportionately benefit from welfare turns whites against supporting welfare policies in general (Fox 2004; Gilens 2000; Winter 2006). Yet Alesina and Glaeser's warning overlooks that what democratic institutions preclude with respect to race, is possible in terms of foreign citizens and immigrants: Rather than abandoning the welfare system altogether, welfare chauvinism allows maintaining a strong welfare state while limiting its universal character, that is, it excludes the unwanted. European scholars have paid particular attention to

the phenomenon, studying both trends towards welfare chauvinistic policies (Keskinen, Norocel, and Jørgensen 2016) and welfare chauvinistic attitudes among the European public (Kulin et al. 2016; van Oorschot 2008b).

The theory of the deservingness heuristic is the standard approach to explain how people form welfare opinions – including welfare chauvinistic attitudes (Feather 1999; van Oorschot 2000). According to this theory, people assess the degree to which a person or a group deserves welfare support by considering five criteria: their level of need, their responsibility for and control over this hardship, reciprocity with respect to the welfare system, stereotypes about their typically (anti-)social behavior towards society, and finally their ethnic background. Some further consider whether the person or group shows effort to get out of their situation of need (DeSante 2013), but it is questionable whether this is a dimension that is theoretically distinct from that of responsibility and control. Focus group research suggests that people consider especially past and not potential future contributions to the welfare system, when they consider the dimension of reciprocity (Laenen et al. 2019). Against this background, it is only welfare chauvinism proper, if someone sees immigrants as less deserving of welfare support because of their ethnic background, which defines them as not 'our own'. That said, because people also use group stereotypes in their evaluation of deservingness, welfare chauvinism may also be rooted in regarding immigrants as not having contributed to the welfare system enough, being anti-social free riders, or self-responsible for their situation of need. Careful research needs to disentangle these theoretically distinct drivers of welfare chauvinism.

Initial studies asked respondents to compare immigrants to groups such as the elderly or the unemployed and shows that immigrants tend to be ranked by Europeans among the least deserving of welfare support (van Oorschot 2006, 2008b). However, more recently scholars have come to see these comparisons as biased, because being an immigrant implies no situation of need and thus also no deservingness (Kootstra 2016). Scholars have therefore moved on to using survey experiments in which respondents are presented with fictional vignettes of individuals who are in comparable situations of need and responsibility (e.g., are unemployed) but differ with respect to their ethnic background and length of residence. These experimental studies consistently show that majority members regard ethnic minorities and recent immigrants as less deserving of welfare (Buss 2019; Ford 2016; Gilens 1996; Hjorth 2016; Kootstra

2016; van der Meer and Reeskens 2020; Reeskens and van der Meer 2019).[1] By experimentally disentangling immigration status and ethnic background while holding the other dimensions of deservingness constant, these studies on welfare deservingness imply that immigrants are regarded as less deserving of welfare partly because of a perceived lack of reciprocity to the welfare system stemming from their limited time in the country but also because of their ethnic background. Thus, there is racism-driven welfare chauvinism proper and reciprocity-motivated welfare chauvinism against immigrants.

Recent focus group research emphasizes that the different dimensions of deservingness should not be regarded as working independently from one another (Nielsen, Frederiksen, and Larsen 2020). Some experimental studies indeed investigate joint interaction effects of the different deservingness dimensions. That is, they test whether reciprocity-motivated and racism-driven welfare chauvinism reinforce each other, or whether ethnic minorities face extra penalties for failing on one of the other dimensions of deservingness. The latter may be regarded as indicative about the importance of stereotypes, under the assumption that ethnic minorities face extra penalties because certain shortfalls are regarded as symptomatic for them but exceptional for mainstream majority members. Extra penalties may then be motivated as sanctioning ethnic minorities into assimilating to the perceived norm among the mainstream. The findings do not paint a clear picture. Kootstra (2016) reports that ethnic minorities are indeed regarded as even less deserving if they have recently immigrated (but see Ford 2016), and also that a shorter work history (another indicator of reciprocity) is a stronger liability for such minorities. Her experiment further suggests ethnic minorities face extra penalties for showing little effort to find new employment. This finding is also supported by Reeskens and van der Meer (2019), although they do not find an extra ethnic penalty for their second indicator of responsibility, unemployment due to poor work ethos. Regarding healthcare chauvinism during the COVID-19 pandemic in

---

[1] A related line of survey experimental work demonstrates that majority members support for universal welfare policies declines if typical benefits claimants are portrayed as immigrants (Bay, Finseraas, and Pedersen 2016; Bay and Pedersen 2006; Goerres, Karlsen, and Kumlin 2020), which parallels US research on welfare being "coded" as Black (DeSante 2013; Fox 2004; Gilens 1996; Winter 2006). There is also experimental work on which immigrants are regarded as deserving citizenship (Hainmueller, Hangartner, and Yamamoto 2015), permanent residence (Czymara and Schmidt-Catran 2017), entry to a country (Diehl, Hinz, and Auspurg 2018), and which refugees are seen as deserving asylum (Bansak, Hainmueller, and Hangartner 2016; Hager and Veit 2019). However, these studies do not need to ensure comparability between vignettes describing immigrants as compared to co-ethnic and native born persons.

particular, Larsen and Schaeffer's (2020) survey experiment on who deserves hospital care reveals no blatant racism against Danish born Muslims but suggests that recent immigrants are regarded as less deserving of hospital treatment – especially if they have a Muslim name.[2]

However, one gap in the previous experimental literature on welfare chauvinism is that, to the best of our knowledge, the deservingness dimension of stereotypes about (anti-)social behavior towards society has so far been neglected – unless one regards the effort and poor work ethos treatments as also indicative of this dimension. Yet, it has not explicitly been held constant or randomized. We can therefore not exclude that the general findings about reciprocity-motivated and racism-driven welfare chauvinism are partly driven by stereotypes about immigrants and ethnic minorities as being anti-social towards society, nor do we know whether ethnic minorities face extra penalties for such antisocial behavior.

Vaccination Chauvinism During the COVID-19 Pandemic in Denmark?

The Danish COVID-19 vaccination program is a particularly well-suited case to study welfare chauvinism and the role of stereotypes about anti-social behavior towards society. Denmark does not only represent the social-democratic (i.e., Nordic) welfare regime with a national healthcare system that offers universal coverage to its residents, but also has a recent history of introducing welfare chauvinistic policies, which are arguably particularly targeted at Muslim immigrants.

Denmark is a social-democratic welfare regime (Esping-Andersen 1990) and thus represents the comprehensive welfare state which scholars and pundits who discuss welfare and immigration typically have in mind. As a strongly intervening state, Denmark regulates its labor market by participating as a mediator in the public bargaining negotiations between unions and employer associations and provides universal and generous welfare, especially to families with children. It finances this regime via high redistributive taxes and strong incentives for full employment – among all genders (Schröder 2019). The national healthcare system, which offers equal and generally

---

[2] In a recent webinar on "Experimental research on popular attitudes toward the COVID-19 pandemic" organized by Carlo Knotz and Flavia Fossati, several authors presented related findings according to which immigrants are regarded as less deserving of hospital care or an early vaccination. Yet, the presented studies do not disentangle immigrant status from ethnic background and stereotypes about these minorities.

free access to all residents of Denmark, is a cornerstone of this welfare regime. During the COVID-19 pandemic, the healthcare system not only guarantees free and equal medical treatment, but also has one of the world's highest COVID-19 testing rates thanks to its free of charge COVID-19 testing centers (Hasell et al. 2020). The Danish COVID-19 vaccination program is also free of charge and according to the Danish Health Authority prioritizes target groups to minimize death and severe illness, the spread of infection, and ensure key societal functions.[3]

Nevertheless, welfare chauvinism has made its way into Danish public opinion and politics over the past decades (Bay, Finseraas, and Pedersen 2013). Among other things, welfare benefits have been cut by half for refugees and recent immigrants with the declared goal to incentivize fast employment and self-sufficiency. Several of these policy reforms are arguably targeted at Muslims. The 225 hour rule, for example demands each partner in a union to have worked for at least 225 hours over the past twelve months so that each can receive full welfare benefits (Jørgensen and Emerek 2014). This policy affected Muslim families in particular, because of the low labor force participation rates among Muslim women. Muslims, who make ca. 5% of the Danish population (Jacobsen 2015; Jacobsen and Vinding 2019), also stand center stage in public discourse (Rytter and Pedersen 2014). In Denmark, with its strong emphasis on free speech and gender equality, the conflict following the Muhammad caricatures of Jyllands-Posten (Sniderman et al. 2014), the low employment rates among Muslim women (Caswell, Kleif, and Jensen 2008), or recent reports of Sharia courts discriminating women (Kamil and Pramming 2016) have continuously fueled a controversial discourse, portraying Muslims as antisocial free riders that benefit from welfare over-proportionally while maintaining patriarchic family structures. The outbreak of the COVID-19 pandemic is no exception to this. So called non-Western immigrants, the majority of which are Muslims, have been criticized in news articles for their overrepresentation in hospitalizations (DR news 2020) and singled out as anti-social and irresponsible after an early COVID-19 outbreak in Århus following two funerals (Birk 2020).

---

[3] https://www.sst.dk/en/English/Corona-eng/Vaccination-against-COVID-19

Hypotheses

In summary, we discussed the five dimensions of deservingness theory and the recent survey experimental literature testing it as an explanation of welfare chauvinism. We noted the gap that prior research does not explicitly engage with the dimension of stereotypes about anti-social behavior and whether ethnic minorities face extra penalties for such behavior. We then introduced the case of the Danish COVID-19 vaccination as a well-suited case to study these ideas that overcomes a limitation of prior research. Based on these considerations, we formulated overall fifteen directed hypotheses in our publicly accessible pre-registration.[4] For reasons of brevity, we only summarize those with a focus on welfare chauvinism here.

First, if concerns about reciprocity (i.e., low prior contributions to the welfare system) drive deservingness, then *persons who have immigrated to Denmark only one year ago are seen as less deserving of an early COVID-19 vaccination than persons who were born domestically*. Second, if racism drives deservingness, then *persons with a typical Muslim name are seen as less deserving of an early COVID-19 vaccination than persons with a typical Nordic name*. Third, if concerns about reciprocity and racism reinforce each other in a joint effect, then *there is an aggravating (negative) interaction effect between being a recent immigrant and having a Muslim name*. Fourth, if certain anti-social or irresponsible behaviors are regarded as symptomatic for immigrants/Muslims but exceptional for mainstream Danes, then *there are aggravating (negative) interaction effects between being a recent immigrant/having a Muslim name and having diabetes because of an unhealthy lifestyle or not having followed the social distancing and mask wearing guidelines in the past half year*. Finally, if reciprocity-driven and racism-motived welfare chauvinism are very strong, then *recent immigrants or persons with a Muslim name are even seen as less deserving if they live up to the remaining deservingness criteria*, that is, have a Nordic name/were born domestically, have diabetes despite a healthy lifestyle, and followed the social distancing and mask wearing guidelines closely.

---

[4] https://osf.io/kf32y/?view_only=95c5b7997264456eb91435bd99490e1c

Data and Methods

To test our hypotheses, we designed a paired-vignette with forced choice online survey experiment on who should get vaccinated against COVID-19 first.[5] Compared to standard single vignette survey experiments, paired-vignette designs have been shown to generate more valid results (Hainmueller, Hangartner, and Yamamoto 2015). Our target population were the non-immigrant-origin residents of Denmark during the final days before and during the first period after the first person was vaccinated in Denmark on 27 December 2020. Our study thus takes advantage of a unique moment in time when stakes about who would get access to a vaccine at which point in time were high. That said, one might be concerned whether this frames our results as less generalizable. This concern is of course true for any research on special events. However, Appendix B shows that the main findings do not change over the course of the study period, and Helbling et al.'s (2021) show that their findings on healthcare chauvinism do not even change over the course of a year. We pre-registered our experimental design, hypotheses, sample definition, and estimation strategy on 19 December 2020, two days before data collection started. The pre-registration is openly accessible on the Open Science Framework.[6] The Online Supplement to this article contains the raw data as delivered by Epinion on 30 December 2020 and the R code that replicates our findings and additional results.

Experimental design

Our experimental design started by introducing participants to some brief background information on the Danish COVID-19 vaccination program, closely echoing information from the official homepage of the Danish Health Authority (see pre-registration for details). After the introduction, participants were posed three (pre-treatment) survey questions about their opinion on getting vaccinated against COVID-19, worries about possible side-effects, and their expectation of whether the majority of the population will be vaccinated by the end of June. Appendix B in the Online Supplement shows that the main findings are robust to excluding respondents who do not wish to get

---

[5] This study was not subject to ethical review. The Research Ethics Committee of our faculty explicitly states that ethical review is targeted at grant proposals and takes "some months' processing time", which conflicts with the timely nature of our study. That said, we believe our study lives up to all of the principles outlined in the Menlo Report (2012): the participants were not sampled among vulnerable groups, there was informed consent, no deception, participants were surveyed as autonomous agents about their attitudes, they were not posed to harm, and we did not restrict their autonomy.

vaccinated, who are very afraid of the vaccine, or who think that the majority of the population will be vaccinated in the first half of 2021 and may thus not see the immediacy of the problem.

After answering the three questions participants were prompted to a second page, which explained the immediacy of the situation given the initially limited numbers of doses and then introduced the respondents to the paired-vignette choice task following on the upcoming three pages. On each of the following three pages, the participants were then shown two brief vignettes of above-mentioned diabetes patients and asked to choose which one of the two, they think should get vaccinated first:

> "We would like to ask you, who of these two persons you think should get vaccinated first?
>
> [*Name*] is 55 years old and works as a cashier in a supermarket. He [*Length of residence*]. Over the past half year, he has [*Good citizen*] careful to follow the guidelines on facemask wearing and social distancing. [*Name*] has diabetes [*Healthy lifestyle*]."

The binary answer indicating which of the two profiles was chosen, is our dependent variable. Our forced choice experiment did not allow the participants to skip the choice or to answer that they do not know who to choose. By stating that all persons are diabetes patients with a high risk of facing a severe COVID-19 infection, we held the deservingness dimension of need constant. The vignettes randomly varied the remaining four dimensions of deservingness theory with two levels each, resulting in a 2 x 2 x 2 x 2 (= 16) full factorial design. To ensure proper and orthogonal randomization of the four treatments, we used block randomization, where participants were randomly assigned to three out of overall 240 (= 16 * (16 - 1)) equally sized and thus probable blocks of paired-vignettes. During the course of fieldwork, the block randomization adopted to survey non-continuation to guarantee equal probability across the blocks and thus orthogonality of the treatment conditions in the final sample.

We randomly varied the vignettes in the following ways. First, we followed the example of Larsen and Schaeffer (2020) and altered the persons names as typical Muslim or Nordic and their length of residence in Denmark as either "was born in Denmark" or "has lived in Denmark for one year". In line with prior research, these two treatment

dimensions are meant to measure the ethnic background and reciprocity dimension of deservingness theory, respectively. For the name treatment, we use a randomized pool of three names per level to avoid estimating a name-specific instead of a general ethnic background effect. Again following Larsen and Schaffer (2020) who selected names based on frequency in the Danish population, the names were Jørgen, Hans, and Erik as compared to Mustafa, Ibrahim, and Ahmad.[6] We further introduced two new treatments. Like Reeskens et al. (2021), who do not focus on welfare chauvinism however, we vary whether the person has lived up to COVID-19 guidelines. But in contrast to their treatment about abstaining from an international holiday trip to Barcelona, we varied whether the person has "not been" or "been very" careful to follow the guidelines on facemask wearing and social distancing because our goal was to rather tap into typical stereotypes about Muslims' and immigrants' anti-social behavior towards society. Our treatment clearly frames the person as an anti-social free rider who nevertheless benefits from the huge collective efforts and immense costs to keep the spread of COVID-19 at bay. Finally, we varied the dimension of responsibility for one's situation of need, by explaining that the person has diabetes "despite his healthy lifestyle; he does not smoke and exercises regularly" or "because of his unhealthy lifestyle; he smokes and does not exercise". Note that our vignette holds two further important pieces of information constant. All persons are described as being 55 years of age and as cashiers in a supermarket. Holding age constant is important because older people are seen as less deserving of critical healthcare during the pandemic (Helbling et al. 2021; Larsen and Schaeffer 2020). Holding employment constant is important because of the higher unemployment rate among Muslims in Denmark so that ethnic background effects might be intermingled with reciprocity effects.

Sample

The target population of our study were persons of at least 18 years of age, who were born in Denmark and whose parents were both also born in Denmark, and who lived in a private home in Denmark during the final days before and after the first person

---

[6] All names were male, because considering gender would have doubled the treatment levels from 16 to 32 and thus resulted in need for a larger sample size. However since Muslim men face harsher labor market discrimination (Dahl and Krog 2018), we chose the gender that is likely to cause stronger treatment effects. Recently name-based studies have come under critique because minority names may signal both ethnic but also working class background (Gaddis 2017; Wenz and Hoenig 2020). But because neither Dahl and Krog (2018) nor Larsen and Schaeffer (2020) find that considering middle and working class names matters in the Danish context, we kept our design simple.

was vaccinated in Denmark on 27 December 2020. As part of our pre-registration we conducted a statistical power analysis for conjoint experiments (Schuessler and Freitag 2020) and pre-registered a sample of 2,500 respondents. This sample size implies that we can identify a true treatment effect of 5% with a probability close to one. Yet when it comes to a true interaction effect of 5%, we can accurately identify it with a probability of 0.58 (two-tailed) to 0.7 (one-tailed). Overall, 2,514 Participants were recruited by the survey company Epinion from an ongoing online panel and did not receive an incentive for their participation. The panelists are a stratified (i.e., by age, gender, and education) random probability sample from the Danish registers. The data contains post-stratification weights to further ensure representativity. Data collection started on 21 December 2020 and was finalized on 30 December. To alleviate the concern of so-called survey speeders, Epinion removes the top 2.5% fastest respondents from the sample before data delivery. In addition to this, Appendix C of the Online Supplement analyses response times and demonstrates that the results are by and large robust to the excluding of very fast and very slow respondents.

Estimation strategy

Our goal is to identify average marginal component (interaction) effects for the four profile attributes. Because these are equivalent to OLS estimates (Egami and Imai 2019; Hainmueller, Hopkins, and Yamamoto 2014), we use post-stratification weighted OLS regression with robust standard errors clustered on the respondent level (because of the repeated choice tasks) to analyze the data. To identify average marginal component effects, we estimate a model without any interaction effects. To identify average marginal component interaction effects, we estimate single models testing one interaction effect at a time, resulting in five further models. The data also contain information on respondents' socio-demographic characteristics: gender, age, education, region, number of persons in the household, and the day of their interview. Appendix D in the Online Supplement shows that these variables are balanced across the treatment conditions. Their consideration in the regression models does not alter the results. Since the experimental data and the socio-demographics contain no missing values, there is no need to impute values or delete cases.

Results

Are recent immigrants and Muslim minorities regarded as less deserving of critical access to preventive healthcare amid the COVID-19 pandemic? Figure 1 shows the average marginal effects of the four treatment dimensions of our paired-vignette experiment, which holds the situation of need constant and disentangles the two minority statuses from one another as well as from stereotypes about anti-social and irresponsible behaviors. With regards to our initially-raised question, we first see that – all else being equal – having a Muslim name indeed lowers one's probability by 4.6% to be seen as deserving an early COVID-19 vaccination. Albeit being by far the smallest effect, one should keep in mind that this finding is triggered simply by a Muslim rather than a Nordic name, as potential stereotypes about unemployment, anti-social and irresponsible behavior, and time in spent in Denmark are held constant. This finding thus suggests that blatant racism partly drives considerations about healthcare deservingness. Reciprocity-driven chauvinism is stronger, as indicated by our finding that recent immigrants face considerably more resentment. Compared to those born in Denmark, recent immigrants are 13.6% less likely to be regarded as deserving an early COVID-19 vaccination. These two findings confirm our pre-registered hypotheses about racism-driven and reciprocity-motivated healthcare chauvinism. Exploratory analyses reported in Appendix E in the Online Supplement suggest that racist-driven healthcare chauvinism against Muslims is more pronounced among the less educated and among men, while reciprocity-motivated healthcare chauvinism against recent immigrants is more pronounced among women. We find no effect heterogeneity by age.

Figure 1: Average marginal component effects on who should get vaccinated first

Difference (in %) to person with reference value
(i.e., healthy lifestyle, Nordic name, born in DK, or followed guidelines)
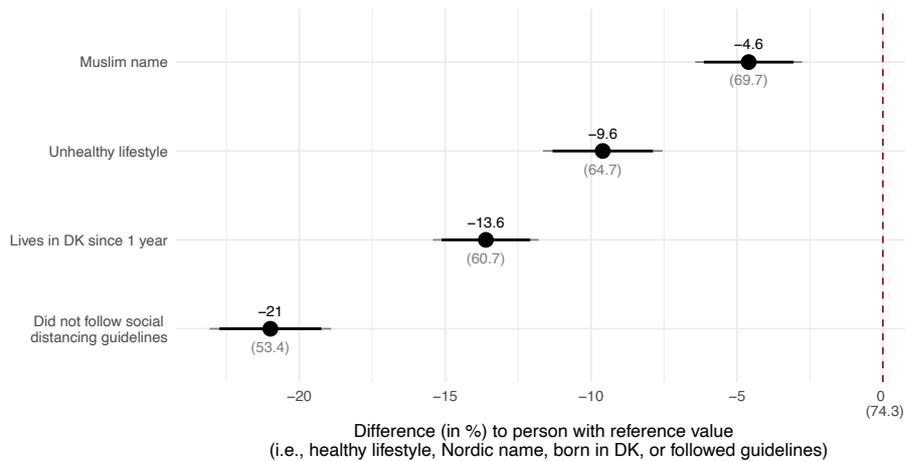
Note: Average marginal component effects and associated 90 and 95% (two-tailed) confidence intervals based on post-stratification weighted OLS regression with cluster-robust standard errors. Full regression results are shown in Appendix A Table 1 of the Online Supplement.

Figure 1 contains two further noteworthy findings, which are perfectly in line with deservingness theory. Patients having diabetes because of their unhealthy lifestyle and who are thus at least partially responsible for facing an increased risk of a severe COVID-19 infection, are regarded as less deserving of an early COVID-19 vaccination. Yet with an effect size of 21%, the by far strongest factor affecting deservingness is whether the patient has followed the guidelines on facemask wearing and social distancing – a rather noteworthy finding given that the dimension of (anti-)social behavior has been largely neglected in prior work. This raises the important question, whether Muslims and recent immigrants face over-proportional resentment if they show these forms of anti-social and irresponsible behavior? As elaborated in our theory section, there is good reason to believe that recent immigrants and Muslims are penalized more harshly, if anti-social or irresponsible behaviors are regarded as symptomatic for immigrants or Muslims.

Figure 2 visualizes interaction effects of the four treatment dimensions and thus answers the raised question. Overall, the evidence is not strong. First, we see that a prior finding of Larsen and Schaffer (2020; see also Kootstra 2016) does not replicate. In contrast to their survey experiment on hospital care, having a Muslim name does

14

not amplify the effect of having recently immigrated and vice versa. We thus cannot re-confirm that racism-driven and reciprocity-motivated chauvinism reinforce each other when it comes to the question of who deserves early vaccination. Yet, we do find some evidence of extra ethnic and immigrant penalties for anti-social and irresponsible behavior respectively. Recent immigrants face an extra 3% penalty for having an unhealthy lifestyle as compared to those born domestically. This finding may reflect concerns over healthcare tourism, that is, the fear physically vulnerable immigrants could take residence in Denmark with its generous and universal (national) healthcare system (cf., Hjorth 2016). By comparison, Muslims face a 3.3% extra penalty for not having followed facemask wearing and social distancing guidelines compared to diabetes patients with a Nordic name. This finding in turn may reflect stereotypes about Muslims as anti-social free riders. Note however that both findings only pass conventional levels of statistical significance because they test pre-registered and directed hypotheses ($p_{\text{Unhealthy lifestyle, two-tailed}} = 0.0914$ versus $p_{\text{Unhealthy lifestyle, one-tailed}} = 0.0457$, and $p_{\text{Guidelines, two-tailed}} = 0.0591$ versus $p_{\text{Guidelines, one-tailed}} = 0.0296$). Moreover, while it seems plausible that immigrants wake fears of healthcare tourism while anti-social behavior is seen as symptomatic among Muslims, one should be patient whether ad-hoc we would not have seen the opposite pattern as plausible, too. We thus consider the assumption of extra penalties as tentatively confirmed but also of needing further investigation.

Figure 2: Average marginal component interaction effects on who should get vaccinated first
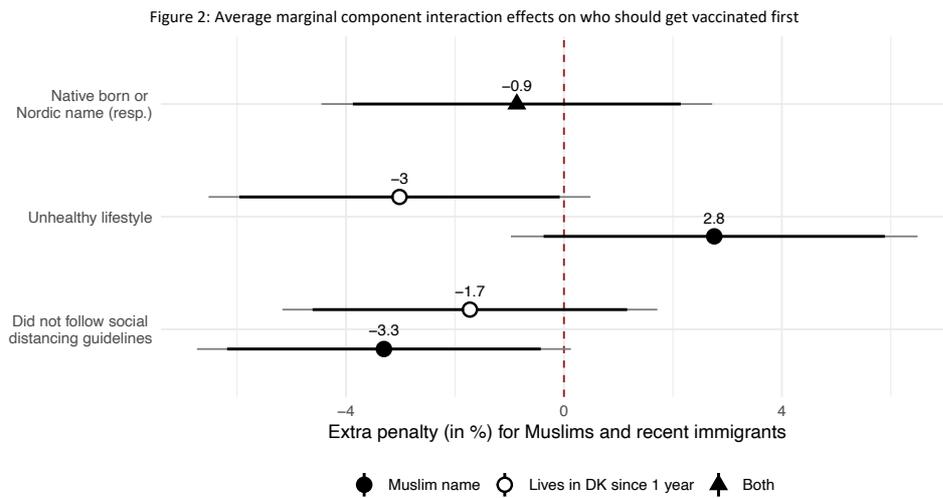

Note: Average marginal component interaction effects and associated 90 and 95% (two-tailed) confidence intervals based on post-stratification weighted OLS regression with cluster-robust standard errors. Full regression tables are shown in Appendix A Table 2 of the Online Supplement.

Our findings of extra penalties, although tentative, raise the final question of the consistency of blatant racism and reciprocity-motivated chauvinism. That is, if we condition on the sub-population of patients who should be deserving because of their healthy lifestyle or because they have followed the guidelines, do we still observe racism-driven and reciprocity motivated healthcare chauvinism? The top panel of Figure 3 visualizes estimates of the deservingness gap that Muslims and immigrants face under all conditions that should frame them as deserving of an early vaccination. The bottom panel extends this analysis to all combinations of these favorable conditions.[7] The top panel reports the results of a pre-registered confirmatory and the bottom panel of an exploratory analysis. While Figure 2 tells us about extra penalties, Figure 3 teaches us the sobering lesson that recent immigrants are systematically regarded as less deserving of an early vaccination, regardless of whether we zoom in on those who fulfill any or several of the other deservingness dimensions. The same basically holds for Muslims, with the single exception of native-born Muslims who have carefully followed the social distancing guidelines; they do not face a systematic deservingness

---

[7] Note that we refrained from estimating the four-way interaction between all components because statistical power is already quite low for the three-way interactions.

gap to native born patients with a Nordic name who also has followed the guidelines. Overall, we find consistent evidence of both blatant racism-driven and reciprocity-driven healthcare chauvinism even when we focus on patients fulfilling other deservingness criteria, such as being native-born, having a Nordic name or being a socially minded patient with a responsibly healthy lifestyle.

Figure 3: Average marginal component main effects on who should get vaccinated first
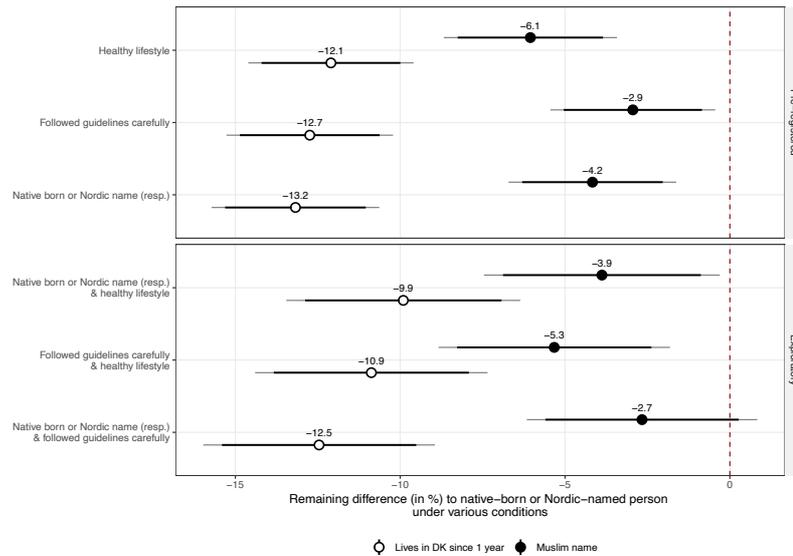

Note: Average marginal component interaction effects and associated 90 and 95% (two-tailed) confidence intervals based on post-stratification weighted OLS regression with cluster-robust standard errors. Full regression tables are shown in Appendix A Table 2 of the Online Supplement.

Conclusion

Our paired-vignette experiment affirms systematic welfare chauvinism among the population of a comprehensive Nordic welfare state. All else being equal, non-immigrant origin Danes regard diabetes patients with a Muslim name or who have recently immigrated as less deserving of an early vaccination against a likely severe COVID-19 infection. These results are very persistent and even hold if we focus on the subset of vignettes describing socially minded patients with a responsibly healthy lifestyle who were born domestically or have a Nordic name respectively. Moreover, we find suggestive evidence that Muslims are further penalized if they have not followed facemask wearing and social distancing guidelines, while immigrants face extra penalties if their unhealthy lifestyle is partly responsible for their diabetes. These results suggest that

in addition to racist-driven and reciprocity motivated welfare chauvinism, stereotypes about Muslims being symptomatically antisocial free riders and immigrants engaging in healthcare tourism seem to matter, too.

Our results are noteworthy because they attest welfare chauvinism proper with respect to the arguably most important measure of preventive public healthcare amid a pandemic. In addition to its timely and socially significant nature, our experiment is furthermore situated in an ideal-typical welfare state and focuses on a minority population that stands center stage in public discourse on welfare burdens. At the same time, one should mention that the unique focus on chauvinism against preventive healthcare during a pandemic also means that our results do not easily generalize to other welfare policies typically studied. Our theoretical albeit empirically untested claim is: if we observe chauvinism even in these dire times and for this specific scenario, it is a pervasive public opinion that falls short of the equality guaranteed by democratic institutions and debunks justifications of chauvinistic policies as furthering integration as lip service.

Our study also contributes to research on welfare chauvinism by disentangling Muslim and immigrant minority status from stereotypes about unemployment as well as irresponsible and especially anti-social behavior. Particularly the latter has been neglected in prior research but figures as a decisive dimension in our study. Moreover, our investigation of extra penalties for these behaviors advances recent attempts to study the joint effects of different deservingness dimensions. That said, not only is our evidence on these joint effects somewhat frail and needs further investigation, we also cannot replicate the prior finding that ethnic background and immigrant status reinforce each other (Kootstra 2016; Larsen and Schaeffer 2020). This suggests that both research on welfare chauvinism and deservingness theory might benefit from further explicating reinforcing joint effects and their scope conditions; an insight echoed in two recent and independent focus group analyses on the topic (Laenen et al. 2019; Nielsen et al. 2020). But it also shows the need for replication and meta-analyses.

References

Alesina, Alberto, and Edward Glaeser. 2004. *Fighting Poverty in the US and Europe*. Oxford: Oxford University Press.

Andersen, Jørgen Goul, and Tor Bjørklund. 1990. "Structural Changes and New Cleavages: The Progress Parties in Denmark and Norway." *Acta Sociologica* 33(3):195–217. doi: 10.1177/000169939003300303.

Bansak, Kirk, Jens Hainmueller, and Dominik Hangartner. 2016. "How Economic, Humanitarian, and Religious Concerns Shape European Attitudes toward Asylum Seekers." *Science* 354(6309):217–22. doi: 10.1126/science.aag2147.

Bay, Ann-Helén, Henning Finseraas, and Axel West Pedersen. 2016. "Welfare Nationalism and Popular Support for Raising the Child Allowance: Evidence from a Norwegian Survey Experiment." *Scandinavian Political Studies* 39(4):482–94. doi: 10.1111/1467-9477.12067.

Bay, Ann-Helén, and Axel West Pedersen. 2006. "The Limits of Social Solidarity: Basic Income, Immigration and the Legitimacy of the Universal Welfare State." *Acta Sociologica* 49(4):419–36. doi: 10.1177/0001699306071682.

Birk, Christian. 2020. "Omstridt imam lavede skilsmissekontrakt, hvor muslimsk kvinde kunne miste børnene: »Det er psykisk vold udført med en shariakontrakt«." *Berlingske.dk*. Retrieved October 13, 2020 (https://www.berlingske.dk/content/item/1506616).

Buss, Christopher. 2019. "Public Opinion towards Targeted Labour Market Policies: A Vignette Study on the Perceived Deservingness of the Unemployed." *Journal of European Social Policy* 29(2):228–40. doi: 10.1177/0958928718757684.

Caswell, Dorte, Helle Bendix Kleif, and Kræn Blume Jensen. 2008. "Familieforsørgede Indvandrerkvinders Muligheder Og Barrierer i Forhold Til Beskæftigelse Og Uddannelse."

Czymara, Christian S., and Alexander W. Schmidt-Catran. 2017. "Refugees Unwelcome? Changes in the Public Acceptance of Immigrants and Refugees in Germany in the Course of Europe's 'Immigration Crisis.'" *European Sociological Review* 33(6):735–51. doi: 10.1093/esr/jcx071.

Dahl, Malte, and Niels Krog. 2018. "Experimental Evidence of Discrimination in the Labour Market: Intersections between Ethnicity, Gender, and Socio-Economic Status." *European Sociological Review* 34(4):402–17. doi: 10.1093/esr/jcy020.

DeSante, Christopher D. 2013. "Working Twice as Hard to Get Half as Far: Race, Work Ethic, and America's Deserving Poor." *American Journal of Political Science* 57(2):342–56. doi: https://doi.org/10.1111/ajps.12006.

Diehl, Claudia, Thomas Hinz, and Katrin Auspurg. 2018. "Who Is Afraid of Skilled Migrants From Europe? Exploring Support for Immigration Control in Switzerland." *Swiss Journal of Sociology* 44(1):59–88. doi: 10.1515/sjs-2018-0004.

Dittrich, David, and Erin Kenneally. 2012. *The Menlo Report: Ethical Principles Guiding Information and Communication Technology Research*. U.S. Department of Homeland Security.

DR news. 2020. "Indvandrere fylder mere i coronastatistik end etniske danskere." *DR*. Retrieved February 1, 2021 (https://www.dr.dk/nyheder/indland/indvandrere-fylder-mere-i-coronastatistik-end-etniske-danskere).

Egami, Naoki, and Kosuke Imai. 2019. "Causal Interaction in Factorial Experiments: Application to Conjoint Analysis." *Journal of the American Statistical Association* 114(526):529–40. doi: 10.1080/01621459.2018.1476246.

Feather, Norman T. 1999. *Values, Achievement, and Justice Studies in the Psychology of Deservingness*. New York: Springer US.

Ford, Robert. 2016. "Who Should We Help? An Experimental Test of Discrimination in the British Welfare State." *Political Studies* 64(3):630–50. doi: 10.1111/1467-9248.12194.

Fox, Cybelle. 2004. "The Changing Color of Welfare? How Whites' Attitudes toward Latinos Influence Support for Welfare." *American Journal of Sociology* 110(3):580–625. doi: 10.1086/422587.

Gaddis, S. Michael. 2017. "How Black Are Lakisha and Jamal? Racial Perceptions from Names Used in Correspondence Audit Studies." *Sociological Science* 4:469–89. doi: 10.15195/v4.a19.

Gilens, Martin. 1996. "'Race Coding' and White Opposition to Welfare." *American Political Science Review* 90(3):593–604. doi: 10.2307/2082611.

Gilens, Martin. 2000. *Why Americans Hate Welfare: Race, Media, and the Politics of Antipoverty Policy*. Chicago: University of Chicago Press.

Goerres, Achim, Rune Karlsen, and Staffan Kumlin. 2020. "What Makes People Worry about the Welfare State? A Three-Country Experiment." *British Journal of Political Science* 50(4):1519–37. doi: 10.1017/S0007123418000224.

Hager, Anselm, and Susanne Veit. 2019. "Attitudes Toward Asylum Seekers: Evidence from Germany." *Public Opinion Quarterly*. doi: 10.1093/poq/nfz023.

Hainmueller, Jens, Dominik Hangartner, and Teppei Yamamoto. 2015. "Validating Vignette and Conjoint Survey Experiments against Real-World Behavior." *Proceedings of the National Academy of Sciences* 112(8):2395–2400. doi: 10.1073/pnas.1416587112.

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):1–30. doi: 10.1093/pan/mpt024.

Hasell, Joe, Edouard Mathieu, Diana Beltekian, Bobbie Macdonald, Charlie Giattino, Esteban Ortiz-Ospina, Max Roser, and Hannah Ritchie. 2020. "A Cross-

Country Database of COVID-19 Testing." *Scientific Data* 7(1):345. doi: 10.1038/s41597-020-00688-8.

Helbling, Marc, Rahsaan Maxwell, Simon Munzert, and Richard Traunmüller. 2021."Does Every Life Count the Same? Evidence from a Triage Experiment," January 21, MZES Uni Mannheim.

Hjorth, Frederik. 2016. "Who Benefits? Welfare Chauvinism and National Stereo-types." *European Union Politics* 17(1):3–24. doi: 10.1177/1465116515607371.

Jacobsen, Brian Arly. 2015. "Islam and Muslims in Denmark." Pp. 171–86 in *After Integration: Islam, Conviviality and Contentious Politics in Europe, Islam und Politik*, edited by M. Burchardt and I. Michalowski. Wiesbaden: Springer Fachmedien.

Jacobsen, Brian Arly, and Niels Valdemar Vinding. 2019. "Denmark" edited by O. Scharbrodt, S. Akgönül, A. Alibašić, J. S. Nielsen, and R. Egdunas. *Yearbook of Muslims in Europe* 11:199–217.

Jensen, Carsten, and Michael Bang Petersen. 2017. "The Deservingness Heuristic and the Politics of Health Care." *American Journal of Political Science* 61(1):68–83. doi: https://doi.org/10.1111/ajps.12251.

Jørgensen, Martin Bak, and Ruth Emerek. 2014. "Ethnic Minorities Among Other Minoritie: A Disfavoured Group in Danish Society?" Pp. 155–66 in *Integration and Protection of Immigrants*. Ashgate.

Kamil, Carolina, and Fannie Isabel Couderc Pramming. 2016. "Det, du kalder sharia-råd, kalder jeg bestyrelser." *Berlingske.dk*. Retrieved February 1, 2021 (https://www.berlingske.dk/content/item/93183).

Keskinen, Suvi, Ov Cristian Norocel, and Martin Bak Jørgensen. 2016. "The Politics and Policies of Welfare Chauvinism under the Economic Crisis." *Critical Social Policy* 36(3):321–29. doi: 10.1177/0261018315624168.

Kootstra, Anouk. 2016. "Deserving and Undeserving Welfare Claimants in Britain and the Netherlands: Examining the Role of Ethnicity and Migration Status Using a Vignette Experiment." *European Sociological Review* 32(3):325–38. doi: 10.1093/esr/jcw010.

Kulin, Joakim, Maureen A. Eger, and Mikael Hjerm. 2016. "Immigration or Welfare? The Progressive's Dilemma Revisited." *Socius: Sociological Research for a Dynamic World* 2:237802311663222. doi: 10.1177/2378023116632223.

Laenen, Tijs, Federica Rossetti, and Wim van Oorschot. 2019. "Why Deservingness Theory Needs Qualitative Research: Comparing Focus Group Discussions on Social Welfare in Three Welfare Regimes." *International Journal of Comparative Sociology* 60(3):190–216. doi: 10.1177/0020715219837745.

Larsen, Mikkel Haderup, and Merlin Schaeffer. 2020. "Healthcare Chauvinism during the COVID-19 Pandemic." *Journal of Ethnic and Migration Studies* 0(0):1–19. doi: 10.1080/1369183X.2020.1860742.

van der Meer, Tom, and Tim Reeskens. 2020. "Welfare Chauvinism in the Face of Ethnic Diversity: A Vignette Experiment across Diverse and Homogenous Neighbourhoods on the Perceived Deservingness of Native and Foreign-Born Welfare Claimants." *European Sociological Review*. doi: 10.1093/esr/jcaa037.

Nielsen, Mathias Herup, Morten Frederiksen, and Christian Albrekt Larsen. 2020. "Deservingness Put into Practice: Constructing the (Un)Deservingness of Migrants in Four European Countries." *British Journal of Sociology* 71(1):112–26. doi: https://doi.org/10.1111/1468-4446.12721.

van Oorschot, Wim. 2000. "Who Should Get What, and Why? On Deservingness Criteria and the Conditionality of Solidarity among the Public." *Policy & Politics* 28(1):33–48. doi: 10.1332/0305573002500811.

van Oorschot, Wim. 2006. "Making the Difference in Social Europe: Deservingness Perceptions among Citizens of European Welfare States." *Journal of European Social Policy* 16(1):23–42. doi: 10.1177/0958928706059829.

van Oorschot, Wim. 2008a. "Solidarity towards Immigrants in European Welfare States." *International Journal of Social Welfare* 17(1):3–14. doi: 10.1111/j.1468-2397.2007.00487.x.

van Oorschot, Wim. 2008b. "Solidarity towards Immigrants in European Welfare States." *International Journal of Social Welfare* 17(1):3–14. doi: 10.1111/j.1468-2397.2007.00487.x.

Reeskens, Tim, and Tom van der Meer. 2019. "The Inevitable Deservingness Gap: A Study into the Insurmountable Immigrant Penalty in Perceived Welfare Deservingness." *Journal of European Social Policy* 29(2):166–81. doi: 10.1177/0958928718768335.

Reeskens, Tim, Femke Roosma, and Evelien Wanders. 2021. "The Perceived Deservingness of COVID-19 Healthcare in the Netherlands: A Conjoint Experiment on Priority Access to Intensive Care and Vaccination." *BMC Public Health* 21(1):447. doi: 10.1186/s12889-021-10488-3.

Schröder, Martin. 2019. "Varieties of Capitalism and Welfare Regime Theories: Assumptions, Accomplishments, and the Need for Different Methods." *KZfSS Kölner Zeitschrift Für Soziologie Und Sozialpsychologie* 71(S1):53–73. doi: 10.1007/s11577-019-00609-7.

Schuessler, Julian, and Markus Freitag. 2020. *Power Analysis for Conjoint Experiments*. SocArXiv.

Sniderman, Paul M., Michael Bang Petersen, Rune Slothuus, and Rune Stubager. 2014. *Paradoxes of Liberal Democracy: Islam, Western Europe, and the Danish Cartoon Crisis*. Princeton University Press.

Wenz, Sebastian E., and Kerstin Hoenig. 2020. "Ethnic and Social Class Discrimination in Education: Experimental Evidence from Germany." *Research in Social Stratification and Mobility* 65:100461. doi: 10.1016/j.rssm.2019.100461.

Winter, Nicholas J. G. 2006. "Beyond Welfare: Framing and the Racialization of White Opinion on Social Security." *American Journal of Political Science* 50(2):400–420. doi: https://doi.org/10.1111/j.1540-5907.2006.00191.x.

Online Supplement to

Who Should Get Vaccinated First? A Conjoint Experiment on Welfare Chauvinism Against Universal Preventive Healthcare During the COVID-19 Pandemic

2021-02-04

Contents

Introduction - Read Me

This online supplement contains results of our main and additional analyses as well as the R code that produces these results based on the raw data that is also part of the online supplement. If you are interested in the results and maybe also in skimming the R code that generates them, you can simply go through this document.

If you wish to replicate the results themselves and maybe alter the R code, you will need to work with the "WhoShouldGetVaccinatedFirst_Analysis_And_Supplements.Rmd" file. To use the Rmd replication file, you need a working version of R (see detailed session info under "Setup" below), RStudio, RMarkdown and Latex. To install RMarkdown and Latex, use the following code after you have installed R and RStudio:

```r
install.packages(c('rmarkdown', 'tinytex'), dep = TRUE)
tinytex::install_tinytex()  # install TinyTeX
```

All mentioned software packages are open source, free to use and available for Windows, Mac Os, and Unix operating systems. Once you have installed these, please open RStudio and establish an RStudio project in the unzipped file directory that contains the "WhoShouldGetVaccinated-First_Analysis_And_Supplements.Rmd" and "03Delivery_VaccineDeservingness_20201230Final.rds" files. For further information on Rstudio projects and how to set them up, please refer to R for Data Science, Chapter 8.

After having set up the RStudio project, you will find all necessary files under the "Files" tab in Rstudio. Open the file "WhoShouldGetVaccinatedFirst_Analysis_And_Supplements.Rmd" by clicking on it under the "Files" tab. The file should open in the top left panel. Rstudio will automatically notify you about all user-written packages that the analysis relies on and that you have not yet downloaded and installed. Please click on "install". To replicate the whole analysis, simply click on "Knit", just below the file tab of the top left panel showing the Rmd file. If you want to alter the R code, you can work on the single R-snippets. For more information on how to edit Rmd files and R snippets see R for Data Science, Chapter 27.

Appendix A: Replication code

Setup

In order to perfectly reproduce our results, you might need to ensure that you use the same versions of R and of the R-packages we used. The session info at the bottom of this code chunk provides all necessary information.

```r
# Libraries
library(tidyverse) ## Data management and cleaning
library(estimatr) ## OLS with robust SE
library(texreg) ## Publication-ready regression tables
library(ggplot2) ## Visualization
library(ggpubr) ## Add several ggplots together
library(car) ## Outlier detection
library(gtsummary) ## Stratified summary statistics


# Show session info on used packages and versions
sessionInfo()
## R version 4.0.3 (2020-10-10)
## Platform: x86_64-apple-darwin17.0 (64-bit)
## Running under: macOS Big Sur 10.16
##
## Matrix products: default
## BLAS:   /Library/Frameworks/R.framework/Versions/4.0/Resources/lib/libRblas.dylib
## LAPACK: /Library/Frameworks/R.framework/Versions/4.0/Resources/lib/libRlapack.dylib
##
## locale:
## [1] en_US.UTF-8/en_US.UTF-8/en_US.UTF-8/C/en_US.UTF-8/en_US.UTF-8
##
## attached base packages:
## [1] stats     graphics  grDevices utils     datasets  methods   base
##
## other attached packages:
##  [1] gtsummary_1.3.6 car_3.0-10      carData_3.0-4   ggpubr_0.4.0
##  [5] texreg_1.37.5   estimatr_0.30.2 forcats_0.5.0   stringr_1.4.0
##  [9] dplyr_1.0.3     purrr_0.3.4     readr_1.4.0     tidyr_1.1.2
## [13] tibble_3.0.5    ggplot2_3.3.3   tidyverse_1.3.0
##
## loaded via a namespace (and not attached):
##  [1] httr_1.4.2          jsonlite_1.7.2      splines_4.0.3
##  [4] modelr_0.1.8        Formula_1.2-4       assertthat_0.2.1
##  [7] cellranger_1.1.0    yaml_2.2.1          pillar_1.4.7
## [10] backports_1.2.1     lattice_0.20-41     glue_1.4.2
## [13] digest_0.6.27       ggsignif_0.6.0      rvest_0.3.6
## [16] colorspace_2.0-0    sandwich_3.0-0      htmltools_0.5.1.1
## [19] Matrix_1.3-2        pkgconfig_2.0.3     broom_0.7.3
## [22] haven_2.3.1         xtable_1.8-4        mvtnorm_1.1-1
## [25] scales_1.1.1        openxlsx_4.2.3      rio_0.5.16
## [28] emmeans_1.5.3       generics_0.1.0      usethis_2.0.0
## [31] ellipsis_0.3.1      TH.data_1.0-10      withr_2.4.1
```

```
## [34] cli_2.2.0          survival_3.2-7    magrittr_2.0.1
## [37] crayon_1.3.4        readxl_1.3.1      estimability_1.3
## [40] evaluate_0.14       fs_1.5.0          fansi_0.4.2
## [43] broom.helpers_1.1.0 MASS_7.3-53       foreign_0.8-81
## [46] rstatix_0.6.0       xml2_1.3.2        data.table_1.13.6
## [49] tools_4.0.3         hms_1.0.0         lifecycle_0.2.0
## [52] multcomp_1.4-15     munsell_0.5.0     reprex_1.0.0
## [55] zip_2.1.1           compiler_4.0.3    rlang_0.4.10
## [58] grid_4.0.3          gt_0.2.2          rstudioapi_0.13
## [61] rmarkdown_2.6       gtable_0.3.0      codetools_0.2-18
## [64] abind_1.4-5         DBI_1.1.1         curl_4.3
## [67] R6_2.5.0            zoo_1.8-8         lubridate_1.7.9.2
## [70] knitr_1.30          stringi_1.5.3     Rcpp_1.0.6
## [73] vctrs_0.3.6         dbplyr_2.0.0      tidyselect_1.1.0
## [76] xfun_0.20           coda_0.19-4
```

Data preparation

The code below details how we reshape the delivered raw data to a long data file where each single vignette is a case alongside an outcome variable indicating whether the respondent selected this vignette to get vaccinated first. Thus we turn the wide data of 2,514 respondents into a long data set of 15,084 vignettes, each of which is embedded in a paired vignette choice with one other vignette and in a respondent with six other vignettes. After that we recode the variables to numeric or factor variables with English labels. All recodings are in line with our the analysis plan stated in our pre-registration [LINK].

```r
# Read the data, make an id, ensure sample definition, and select variables:
#----------------------------------------------------------------------
Vac_data_wide <- readRDS(file = "03Delivery_VaccineDeservingness_20201230Final.rds") %>%
  rowid_to_column(., "id") %>% ## generate a respondent ID,
  ## Ensure sample definition,
  filter(Alder > 17 & bagg5a_2_resp == "Danmark" & bagg5a_3_resp == "Danmark") %>%
  ## keep the following variables,
  select(id, weight, bagg1, Alder, Region, uddannelse_det, bagg4, ActualSurveyStartTime, ActualSu
         starts_with("q1"), starts_with("VignetteExperiment"),
         -ends_with("VersionNumber"), -ends_with("Random")) # finally drop these variables.


# Reshape to long
#----------------
## Rename the vignette experiment variable to ease the reshape
colnames(Vac_data_wide) <- str_remove(colnames(Vac_data_wide), "VignetteExperiment_")
## First reshape: the three tasks per person.
Vac_data_long <- Vac_data_wide %>%
  pivot_longer(cols = -c(id, weight, bagg1, Alder, Region, uddannelse_det,
                         bagg4, ActualSurveyStartTime, ActualSurveyEndTime, starts_with("q1")),
               names_to = c("task", ".value"),
               names_sep = "_") %>%
  ## Second reshape: the two vignettes.
  pivot_longer(cols = -c(id, weight, bagg1, Alder, Region, uddannelse_det,
                         bagg4, ActualSurveyStartTime, ActualSurveyEndTime, starts_with("q1"),
                         Answer, task),
```

4

```r
                names_to = c(".value", "vignette"),
                names_pattern = "([A-Za-z]+)(\\d+)",
                values_drop_na = TRUE)

# Variable recodings
#-------------------
Vac_data_long <- Vac_data_long %>%
  mutate(
    Answer = case_when( ## The binary outcome, was the vignette chosen?
      Answer == "{#Answer2}" & vignette == 1 ~ 0,
      Answer == "{#Answer2}" & vignette == 2 ~ 1,
      Answer == "{#Answer1}" & vignette == 1 ~ 1,
      Answer == "{#Answer1}" & vignette == 2 ~ 0),
    ## The treatments:
    LoR = case_when( ### Immigrant,
      LoR == "har boet i Danmark i ét år" ~ "Lives in DK since 1 year",
      LoR == "er født i Danmark" ~ "Born in DK") %>% factor(),
    Name = case_when( ### Muslim name,
      Name == "1" ~ "Muslim name",
      Name == "2" ~ "Danish/Nordic name") %>% factor(),
    Duty = case_when( ### followed the social distancing guidelines,
      Duty == "været meget" ~ "Followed guidelines carefully",
      Duty == "ikke været" ~ "Did not follow guidelines") %>% factor() %>%
      fct_relevel("Followed guidelines carefully", "Did not follow guidelines"),
    Health = case_when( ### and healthy lifestyle.
      Health == "på trods af sin sunde livsstil; han <b>ryger ikke og dyrker regelmæssigt motion<
      Health == "på grund af sin usunde livsstil; han <b>ryger og dyrker ikke motion</b>" ~ "Unhe
    ## Socio-demographic controls
    Gender = case_when( ### Gender
      bagg1 == "Mand" ~ "Male",
      bagg1 == "Kvinde" ~ "Female") %>% factor(),
    Age = scale(Alder) %>% as.numeric(), ### Age, z-standardized
    Education = case_when( ### Education: Primary, secondary, tertiary.
      uddannelse_det == "Folkeskole / Grundskole" ~ "Primary",
      uddannelse_det == "Gymnasial uddannelse (Student, HF, HH, HTX og lign.)" |
        uddannelse_det == "Erhvervsuddannelse" |
        uddannelse_det == "Kort videregående uddannelse" ~ "Secondary",
      uddannelse_det == "Lang videregående uddannelse (Kandidat niveau)" |
        uddannelse_det == "Mellemlang videregående uddannelse (Bachelor niveau)" ~ "Tertiary") %>
      factor() %>% fct_relevel("Primary", "Secondary", "Tertiary"),
    Pers_HH = case_when( ### Number of persons in the household, z-standardized
      bagg4 == "1 person" ~ 1,
      bagg4 == "2 personer" ~ 2,
      bagg4 == "3 personer" ~ 3,
      bagg4 == "4 personer" ~ 4,
      bagg4 == "5 personer" ~ 5,
      bagg4 == "6 personer eller derover" ~ 6) %>% scale() %>% as.numeric(),
    ## Day of the interview
    Day = as.Date(ActualSurveyEndTime),
```

```
    ## Survey response time
    Responsetime = as.numeric(ActualSurveyEndTime-ActualSurveyStartTime),
    ## Pre-treatment opinions on vaccine.
    q1_1_resp = case_when( ### Want to get vaccinated.
      q1_1_resp == "1 - Helt enig" ~ 5,
      q1_1_resp == "2" ~ 4,
      q1_1_resp == "3" ~ 3,
      q1_1_resp == "4" ~ 2,
      q1_1_resp == "5 - Helt uenig" ~ 1,
      TRUE ~ as.numeric(NA)),
    q1_2_resp = case_when( ### Afraid of side-effects.
      q1_2_resp == "1 - Helt enig" ~ 5,
      q1_2_resp == "2" ~ 4,
      q1_2_resp == "3" ~ 3,
      q1_2_resp == "4" ~ 2,
      q1_2_resp == "5 - Helt uenig" ~ 1,
      TRUE ~ as.numeric(NA)),
    q1_3_resp = case_when( ### Believe majority will be vaccinated until June.
      q1_3_resp == "1 - Helt enig" ~ 5,
      q1_3_resp == "2" ~ 4,
      q1_3_resp == "3" ~ 3,
      q1_3_resp == "4" ~ 2,
      q1_3_resp == "5 - Helt uenig" ~ 1,
      TRUE ~ as.numeric(NA)))
```

Regression analysis

To analyze the experimental data, we run post-stratification weighted OLS (i.e., linear probability) regression with robust standard errors. Specifically, we run two models. A baseline specification entails no control variables and the second specification adds control variables. The results are virtually the same. The figures displayed in the main article are all based on the baseline model.

```
#--------------------------
# 1. "Average effects": AMCE
#--------------------------
## Simple OLS
Mod1 <- lm_robust(
  data = Vac_data_long,
  formula = Answer ~ LoR + Name + Duty + Health,
  clusters = id, weights = weight)
## OLS with controls
Mod1_contr <- lm_robust(
  data = Vac_data_long,
  formula = Answer ~ LoR + Name + Duty + Health +
    Gender + Age + Region + Education + Pers_HH + Day,
  clusters = id, weights = weight)


#--------------------------
# 2. "Extra penalties": AMCIEs
#--------------------------
```

```r
## Simple OLS
Mod2_H5 <- lm_robust(
  data = Vac_data_long,
  formula = Answer ~ LoR*Name + Duty + Health,
  clusters = id, weights = weight)
Mod2_H6 <- lm_robust(
  data = Vac_data_long,
  formula = Answer ~ LoR*Health + Name + Duty,
  clusters = id, weights = weight)
Mod2_H7 <- lm_robust(
  data = Vac_data_long,
  formula = Answer ~ LoR + Name*Health + Duty,
  clusters = id, weights = weight)
Mod2_H8 <- lm_robust(
  data = Vac_data_long,
  formula = Answer ~ LoR*Duty + Name + Health,
  clusters = id, weights = weight)
Mod2_H9 <- lm_robust(
  data = Vac_data_long,
  formula = Answer ~ LoR + Name*Duty + Health,
  clusters = id, weights = weight)
## OLS with controls
Mod2_H5_contr <- lm_robust(
  data = Vac_data_long,
  formula = Answer ~ LoR*Name + Duty + Health +
    Gender + Age + Region + Education + Pers_HH + Day,
  clusters = id, weights = weight)
Mod2_H6_contr <- lm_robust(
  data = Vac_data_long,
  formula = Answer ~ LoR*Health + Name + Duty +
    Gender + Age + Region + Education + Pers_HH + Day,
  clusters = id, weights = weight)
Mod2_H7_contr <- lm_robust(
  data = Vac_data_long,
  formula = Answer ~ LoR + Name*Health + Duty +
    Gender + Age + Region + Education + Pers_HH + Day,
  clusters = id, weights = weight)
Mod2_H8_contr <- lm_robust(
  data = Vac_data_long,
  formula = Answer ~ LoR*Duty + Name + Health +
    Gender + Age + Region + Education + Pers_HH + Day,
  clusters = id, weights = weight)
Mod2_H9_contr <- lm_robust(
  data = Vac_data_long,
  formula = Answer ~ LoR + Name*Duty + Health +
    Gender + Age + Region + Education + Pers_HH + Day,
  clusters = id, weights = weight)

#-----------------------------------------------
```

```r
# 3. "When equal?": Additional exploratory results
#-------------------------------------------------
## Additional exploratory simple OLS models
Mod3_a <- lm_robust(
  data = Vac_data_long,
  formula = Answer ~ LoR*Name*Duty + Health,
  clusters = id, weights = weight)
Mod3_b <- lm_robust(
  data = Vac_data_long,
  formula = Answer ~ LoR*Name*Health + Duty,
  clusters = id, weights = weight)
Mod3_c <- lm_robust(
  data = Vac_data_long,
  formula = Answer ~ LoR*Duty*Health + Name,
  clusters = id, weights = weight)
Mod3_d <- lm_robust(
  data = Vac_data_long,
  formula = Answer ~ LoR + Name*Duty*Health,
  clusters = id, weights = weight)
## Additional exploratory OLS models with controls
Mod3_a_contr <- lm_robust(
  data = Vac_data_long,
  formula = Answer ~ LoR*Name*Duty + Health +
  Gender + Age + Region + Education + Pers_HH + Day,
  clusters = id, weights = weight)
Mod3_b_contr <- lm_robust(
  data = Vac_data_long,
  formula = Answer ~ LoR*Name*Health + Duty +
  Gender + Age + Region + Education + Pers_HH + Day,
  clusters = id, weights = weight)
Mod3_c_contr <- lm_robust(
  data = Vac_data_long,
  formula = Answer ~ LoR*Duty*Health + Name +
  Gender + Age + Region + Education + Pers_HH + Day,
  clusters = id, weights = weight)
Mod3_d_contr <- lm_robust(
  data = Vac_data_long,
  formula = Answer ~ LoR + Name*Duty*Health +
  Gender + Age + Region + Education + Pers_HH + Day,
  clusters = id, weights = weight)
```

Regression tables

In the main article we report all results as coefficient plots. These have the advantage of giving a much more immediate impression of the main results and they are thus more accessible to a wide audience of readers. But since some might be interested in the figures of the point and inference estimates, we report standard regression tables here.

```r
#---------------------------
# 1. "Average effects": AMCE
```

```r
#----------------------------
texreg(
  list(Mod1, Mod1_contr),
  include.ci = FALSE, include.rmse = FALSE, digits = 3,
  doctype = FALSE, stars = c(0.001, 0.01, 0.05, 0.1), symbol = "+",
  custom.coef.names = c("(Intercept)", "Lives in DK for 1 year", "Muslim name",
                        "Did not follow social distancing guidelines",
                        "Has diabetes because of an unhealthy lifesyle",
                        "Male", "Age", "Midtjylland", "Nordjylland",
                        "Sjælland", "Syddanmark", "Upper secondary", "Tertiary",
                        "Number of persons in the household",
                        "Day of survey"),
  groups = list("Treatments" = 2:5, "Region (reference: Hovedstaden)" = 8:11,
                "Education (reference: Primary or less)" = 12:13),
  caption = "Average marginal component effects on who should get vaccinated first",
  caption.above = TRUE)

#----------------------------
# 2. "Extra penalties": AMCIEs
#----------------------------
## Simple OLS
texreg(
  list(Mod2_H5, Mod2_H6, Mod2_H7, Mod2_H8, Mod2_H9),
  include.ci = FALSE, include.rmse = FALSE, digits = 3,
  doctype = FALSE, stars = c(0.001, 0.01, 0.05, 0.1), symbol = "+",
  custom.coef.names = c("(Intercept)", "Lives in DK for 1 year", "Muslim name",
                        "Did not follow social distancing guidelines",
                        "Has diabetes because of an unhealthy lifesyle",
                        "Lives in DK for 1 year * Muslim name",
                        "Lives in DK for 1 year * has diabetes because of an unhealthy lifesyle",
                        "Muslim Name * has diabetes because of an unhealthy lifesyle",
                        "Lives in DK for 1 year * did not follow social distancing guidelines",
                        "Muslim Name * did not follow social distancing guidelines"),
  caption = "Average marginal component interaction effects on who should get vaccinated first",
  caption.above = TRUE, sideways = TRUE, use.packages = FALSE, scriptsize = TRUE)

## OLS with controls
texreg(
  list(Mod2_H5_contr, Mod2_H6_contr, Mod2_H7_contr, Mod2_H8_contr, Mod2_H9_contr),
  include.ci = FALSE, include.rmse = FALSE, digits = 3,
  doctype = FALSE, stars = c(0.001, 0.01, 0.05, 0.1), symbol = "+",
  omit.coef = "(Male)|(Age)|(RegionMidtjylland)|(RegionNordjylland)|(RegionSjælland)|(RegionSydda
  custom.coef.names = c("(Intercept)", "Lives in DK for 1 year", "Muslim name",
                        "Did not follow social distancing guidelines",
                        "Has diabetes because of an unhealthy lifesyle",
                        "Lives in DK for 1 year * Muslim name",
                        "Lives in DK for 1 year * has diabetes because of an unhealthy lifesyle",
                        "Muslim name * has diabetes because of an unhealthy lifesyle",
                        "Lives in DK for 1 year * did not follow social distancing guidelines",
```

```r
                        "Muslim name * did not follow social distancing guidelines"),
      custom.gof.rows = list("Control variables" = c("Yes", "Yes", "Yes", "Yes", "Yes")),
      caption = "Average marginal component interaction effects on who should get vaccinated first in
      caption.above = TRUE, sideways = TRUE, use.packages = FALSE, scriptsize = TRUE)


#-------------------------------------------------
# 3. "When equal?": Additional exploratory results
#-------------------------------------------------
## Simple OLS
texreg(list(Mod3_a, Mod3_b, Mod3_c, Mod3_d),
            include.ci = FALSE, include.rmse = FALSE, digits = 3,
        doctype = FALSE, stars = c(0.001, 0.01, 0.05, 0.1), symbol = "+",
        custom.coef.names = c("(Intercept)", "Lives in DK for 1 year", "Muslim name",
                        "Did not follow guidelines",
                        "Has an unhealthy lifesyle",
                        "Lives in DK for 1 year * Muslim name",
                        "Lives in DK for 1 year * did not follow guidelines",
                        "Muslim name * did not follow guidelines",
                        "Lives in DK for 1 year * Muslim name * did not follow guidelines",
                        "Lives in DK for 1 year * has an unhealthy lifesyle",
                        "Muslim name * has an unhealthy lifesyle",
                        "Lives in DK for 1 year * Muslim name * has an unhealthy lifesyle",
                        "Did not follow guidelines * has an unhealthy lifesyle",
                        "Lives in DK for 1 year * did not follow guidelines * has unhealthy lifes
                        "Muslim name * did not follow guidelines * has an unhealthy lifesyle"),
        caption = "Average marginal component interaction effects on who should get vaccinated fir
        caption.above = TRUE, sideways = TRUE, use.packages = FALSE, scriptsize = TRUE)


## OLS with controls
texreg(list(Mod3_a_contr, Mod3_b_contr, Mod3_c_contr, Mod3_d_contr),
            include.ci = FALSE, include.rmse = FALSE, digits = 3,
        doctype = FALSE, stars = c(0.001, 0.01, 0.05, 0.1), symbol = "+",
        omit.coef = "(Male)|(Age)|(RegionMidtjylland)|(RegionNordjylland)|(RegionSjælland)|(Region
        custom.coef.names = c("(Intercept)", "Lives in DK for 1 year", "Muslim name",
                        "Did not follow guidelines",
                        "Has an unhealthy lifesyle",
                        "Lives in DK for 1 year * Muslim name",
                        "Lives in DK for 1 year * did not follow guidelines",
                        "Muslim name * did not follow guidelines",
                        "Lives in DK for 1 year * Muslim name * did not follow guidelines",
                        "Lives in DK for 1 year * has an unhealthy lifesyle",
                        "Muslim name * has an unhealthy lifesyle",
                        "Lives in DK for 1 year * Muslim name * has an unhealthy lifesyle",
                        "Did not follow guidelines * has an unhealthy lifesyle",
                        "Lives in DK for 1 year * did not follow guidelines * has unhealthy lifes
                        "Muslim name * did not follow guidelines * has an unhealthy lifesyle"),
        custom.gof.rows = list("Control variables" = c("Yes", "Yes", "Yes", "Yes")),
        caption = "Average marginal component interaction effects on who should get vaccinated fir
        caption.above = TRUE, sideways = TRUE, use.packages = FALSE, scriptsize = TRUE)
```

Table 1: Average marginal component effects on who should get vaccinated first

	Model 1	Model 2
(Intercept)	0.743***	2.159
	(0.010)	(6.574)
Treatments		
Lives in DK for 1 year	−0.136***	−0.136***
	(0.009)	(0.009)
Muslim name	−0.046***	−0.046***
	(0.009)	(0.009)
Did not follow social distancing guidelines	−0.210***	−0.210***
	(0.011)	(0.011)
Has diabetes because of an unhealthy lifesyle	−0.096***	−0.096***
	(0.010)	(0.010)
Male		0.004
		(0.002)
Age		−0.002^{+}
		(0.001)
Region (reference: Hovedstaden)		
Midtjylland		−0.002
		(0.003)
Nordjylland		−0.004
		(0.004)
Sjælland		−0.000
		(0.004)
Syddanmark		−0.001
		(0.003)
Education (reference: Primary or less)		
Upper secondary		−0.001
		(0.004)
Tertiary		0.002
		(0.004)
Number of persons in the household		−0.002
		(0.001)
Day of survey		−0.000
		(0.000)
R^2	0.075	0.075
Adj. R^2	0.074	0.074
Num. obs.	15084	15084
N Clusters	2514	2514

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; $^{+}p < 0.1$

Table 2: Average marginal component interaction effects on who should get vaccinated first

	Model 1	Model 2	Model 3	Model 4	Model 5
(Intercept)	0.741***	0.736***	0.751***	0.739***	0.735***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Lives in DK for 1 year	−0.132***	−0.121***	−0.136***	−0.127***	−0.136***
	(0.013)	(0.013)	(0.009)	(0.013)	(0.009)
Muslim name	−0.042**	−0.046***	−0.061***	−0.046***	−0.029*
	(0.013)	(0.009)	(0.013)	(0.009)	(0.013)
Did not follow social distancing guidelines	−0.210***	−0.210***	−0.210***	−0.201***	−0.193***
	(0.011)	(0.011)	(0.011)	(0.014)	(0.014)
Has diabetes because of an unhealthy lifesyle	−0.096***	−0.081***	−0.111***	−0.096***	−0.096***
	(0.010)	(0.014)	(0.014)	(0.010)	(0.010)
Lives in DK for 1 year * Muslim name	−0.009				
	(0.018)				
Lives in DK for 1 year * has diabetes because of an unhealthy lifesyle		−0.030+			
		(0.018)			
Muslim Name * has diabetes because of an unhealthy lifestyle			0.029		
			(0.019)		
Lives in DK for 1 year * did not follow social distancing guidelines				−0.017	
				(0.018)	
Muslim Name * did not follow social distancing guidelines					−0.033+
					(0.017)
R^2	0.075	0.075	0.075	0.075	0.075
Adj. R^2	0.074	0.074	0.074	0.074	0.074
Num. obs.	15084	15084	15084	15084	15084
N Clusters	2514	2514	2514	2514	2514

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; +$p < 0.1$

Table 3: Average marginal component interaction effects on who should get vaccinated first including control variables

	Model 1	Model 2	Model 3	Model 4	Model 5
(Intercept)	2.202	2.167	1.838	2.089	2.637
	(6.580)	(6.581)	(6.594)	(6.571)	(6.580)
Lives in DK for 1 year	−0.132***	−0.121***	−0.136***	−0.127***	−0.136***
	(0.013)	(0.013)	(0.009)	(0.013)	(0.009)
Muslim name	−0.042**	−0.046***	−0.061***	−0.046***	−0.029*
	(0.013)	(0.009)	(0.013)	(0.009)	(0.013)
Did not follow social distancing guidelines	−0.210***	−0.210***	−0.210***	−0.201***	−0.194***
	(0.011)	(0.011)	(0.011)	(0.014)	(0.014)
Has diabetes because of an unhealthy lifesyle	−0.096***	−0.081***	−0.111***	−0.096***	−0.096***
	(0.010)	(0.014)	(0.014)	(0.010)	(0.010)
Lives in DK for 1 year * Muslim name	−0.009				
	(0.018)				
Lives in DK for 1 year * has diabetes because of an unhealthy lifesyle		−0.030+			
		(0.018)			
Muslim name * has diabetes because of an unhealthy lifesyle			0.029		
			(0.019)		
Lives in DK for 1 year * did not follow social distancing guidelines				−0.017	
				(0.018)	
Muslim name * did not follow social distancing guidelines					−0.033+
					(0.018)
Control variables	Yes	Yes	Yes	Yes	Yes
R^2	0.075	0.075	0.075	0.075	0.075
Adj. R^2	0.074	0.074	0.074	0.074	0.074
Num. obs.	15084	15084	15084	15084	15084
N Clusters	2514	2514	2514	2514	2514

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; +$p < 0.1$

Table 4: Average marginal component interaction effects on who should get vaccinated first, additional exploratory results

	Model 1	Model 2	Model 3	Model 4
(Intercept)	0.730***	0.732***	0.724***	0.741***
	(0.013)	(0.013)	(0.013)	(0.013)
Lives in DK for 1 year	−0.125***	−0.099***	−0.109***	−0.136***
	(0.018)	(0.018)	(0.018)	(0.009)
Muslim name	−0.027	−0.039*	−0.046***	−0.053**
	(0.018)	(0.018)	(0.009)	(0.018)
Did not follow guidelines	−0.186***	−0.210***	−0.186***	−0.191***
	(0.018)	(0.011)	(0.019)	(0.018)
Has an unhealthy lifesyle	−0.096***	−0.078***	−0.066***	−0.108***
	(0.010)	(0.019)	(0.018)	(0.019)
Lives in DK for 1 year * Muslim name	−0.006	−0.044$^+$		
	(0.026)	(0.026)		
Lives in DK for 1 year * did not follow guidelines	−0.014		−0.025	
	(0.025)		(0.025)	
Muslim name * did not follow guidelines	−0.030			−0.015
	(0.025)			(0.025)
Lives in DK for 1 year * Muslim name * did not follow guidelines	−0.005			
	(0.036)			
Lives in DK for 1 year * has an unhealthy lifestyle		−0.065**	−0.037	
		(0.025)	(0.025)	
Muslim name * has an unhealthy lifestyle		−0.006		0.048$^+$
		(0.026)		(0.026)
Lives in DK for 1 year * Muslim name * has an unhealthy lifestyle		0.071$^+$		
		(0.036)		
Did not follow guidelines * has an unhealthy lifestyle			−0.030	−0.004
			(0.025)	(0.025)
Lives in DK for 1 year * did not follow guidelines * has an unhealthy lifestyle			0.015	
			(0.035)	
Muslim name * did not follow guidelines * has an unhealthy lifestyle				−0.037
				(0.036)
R^2	0.075	0.075	0.075	0.075
Adj. R^2	0.074	0.075	0.074	0.075
Num. obs.	15084	15084	15084	15084
N Clusters	2514	2514	2514	2514

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; $^+p < 0.1$

Table 5: Average marginal component interaction effects on who should get vaccinated first, additional exploratory results

	Model 1	Model 2	Model 3	Model 4
(Intercept)	2.619	1.858	2.210	2.376
	(6.583)	(6.612)	(6.574)	(6.597)
Lives in DK for 1 year	−0.125***	−0.099***	−0.109***	−0.136***
	(0.018)	(0.018)	(0.018)	(0.009)
Muslim name	−0.027	−0.039*	−0.046***	−0.053**
	(0.018)	(0.018)	(0.009)	(0.018)
Did not follow guidelines	−0.186***	−0.210***	−0.186***	−0.191***
	(0.018)	(0.011)	(0.019)	(0.018)
Has an unhealthy lifesyle	−0.096***	−0.078***	−0.066***	−0.108***
	(0.010)	(0.019)	(0.018)	(0.019)
Lives in DK for 1 year * Muslim name	−0.006	−0.044+		
	(0.026)	(0.026)		
Lives in DK for 1 year * did not follow guidelines	−0.015		−0.025	
	(0.025)		(0.025)	
Muslim name * did not follow guidelines	−0.031			−0.015
	(0.025)			(0.025)
Lives in DK for 1 year * Muslim name * did not follow guidelines	−0.005			
	(0.036)			
Lives in DK for 1 year * has an unhealthy lifesyle		−0.065**	−0.037	
		(0.025)	(0.025)	
Muslim name * has an unhealthy lifesyle		−0.006		0.048+
		(0.026)		(0.026)
Lives in DK for 1 year * Muslim name * has an unhealthy lifesyle		0.070+		
		(0.036)		
Did not follow guidelines * has an unhealthy lifesyle			−0.030	−0.005
			(0.025)	(0.025)
Lives in DK for 1 year * did not follow guidelines * has an unhealthy lifesyle			0.015	
			(0.035)	
Muslim name * did not follow guidelines * has an unhealthy lifesyle				−0.037
				(0.036)
Control variables	Yes	Yes	Yes	Yes
R^2	0.075	0.075	0.075	0.075
Adj. R^2	0.074	0.074	0.074	0.074
Num. obs.	15084	15084	15084	15084
N Clusters	2514	2514	2514	2514

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; +$p < 0.1$

15

Visualization of regression results

In the main article we report the results of our analyses as coefficient plots. Below we display the code
that generates the figures displayed in the main article.

```r
#-------------------------------
# 1. "Average effects": Figure 1
#-------------------------------
## Generate the plotdata
plotdata <- tidy(Mod1) %>%
  filter(term != "(Intercept)") %>%
  mutate(
    min90 = (estimate - qt(0.95, df) * std.error) * 100,
    min95 = (estimate - qt(0.975, df) * std.error) * 100,
    max90 = (estimate + qt(0.95, df) * std.error) * 100,
    max95 = (estimate + qt(0.975, df) * std.error) * 100,
    term = case_when(
      term == "LoRLives in DK since 1 year" ~ "Lives in DK since 1 year",
      term == "NameMuslim name" ~ "Muslim name",
      term == "DutyDid not follow guidelines" ~ "Did not follow social \n distancing guidelines",
      term == "HealthUnhealthy lifestyle" ~ "Unhealthy lifestyle"),
    label_up = round(estimate, digits = 3) * 100,
    label_bottom = paste("(", round(estimate + coef(Mod1)["(Intercept)"], digits = 3) * 100,
                         ")", sep = ""),
    estimate = estimate * 100)

## Plot
ggplot(data = plotdata,
       aes(y = estimate, x = reorder(term, estimate),
           ymin = min90, ymax = max90)) +
  geom_hline(yintercept = 0, color = "#901A1E", lty = "dashed") +
  geom_linerange(aes(ymin = min95, ymax = max95), color = "#808080") +
  geom_pointrange(size = 0.8) +
  geom_text(aes(label = label_up), vjust = -1.2, size = 3) +
  geom_text(aes(label = label_bottom), vjust = 2.2, size = 3, color = "#808080") +
  scale_y_continuous(breaks = c(-25, -20, -15, -10, -5, 0),
                     labels = c("-25", "-20", "-15", "-10", "-5",
                                paste("0 \n (",
                                      round(as.numeric(coef(Mod1)["(Intercept)"]) * 100, digits =
                                      ")", sep = "")))) +
  coord_flip() +
  labs(x = "",
       y = "Difference (in %) to person with reference value
       (i.e., healthy lifestyle, Nordic name, born in DK, or followed guidelines)") +
  theme_minimal()

## Save Figure 1
# ggsave("Figure_1.pdf", plot = last_plot(), width = 8, height = 4)
```

```
#-----------------------------
# 2. "Extra penalties": Figure 2
#-----------------------------
## Generate the plotdata
plotdata <- bind_rows(
  tidy(Mod2_H5)[nrow(tidy(Mod2_H5)),],
  tidy(Mod2_H6)[nrow(tidy(Mod2_H6)),],
  tidy(Mod2_H7)[nrow(tidy(Mod2_H7)),],
  tidy(Mod2_H8)[nrow(tidy(Mod2_H8)),],
  tidy(Mod2_H9)[nrow(tidy(Mod2_H9)),]) %>%
  mutate(
    min90 = (estimate - qt(0.95, df) * std.error) * 100,
    min95 = (estimate - qt(0.975, df) * std.error) * 100,
    max90 = (estimate + qt(0.95, df) * std.error) * 100,
    max95 = (estimate + qt(0.975, df) * std.error) * 100,
    label_up = round(estimate, digits = 3) * 100,
    estimate = estimate * 100,
    which = case_when(
      term == "LoRLives in DK since 1 year:NameMuslim name" ~ "Both",
      grepl("Muslim", term) ~ "Muslim name",
      TRUE ~ "Lives in DK since 1 year") %>%
      factor() %>% fct_relevel("Muslim name", "Lives in DK since 1 year", "Both"),
    term = gsub(".*:","",term),
    term = case_when(
      term == "HealthUnhealthy lifestyle" ~ "Unhealthy lifestyle",
      term == "DutyDid not follow guidelines" ~ "Did not follow social \n distancing guidelines",
      term == "NameMuslim name" ~ "Native born or \n Nordic name (resp.)") %>%
      factor() %>% fct_relevel("Did not follow social \n distancing guidelines", "Unhealthy lifes

## Plot
ggplot(data = plotdata, aes(y = estimate, x = term, shape = which)) +
  geom_hline(yintercept = 0, color = "#901A1E", lty = "dashed") +
  geom_linerange(aes(ymin = min95, ymax = max95), color = "#808080", position = position_dodge(wi
  geom_pointrange(aes(ymin = min90, ymax = max90), position = position_dodge(width = 0.7), fill =
  scale_shape_manual(name = "", values = c(19, 21, 17)) +
  geom_text(aes(label = label_up), position = position_dodge(width = 0.7), vjust = -1.2, size = 3
  coord_flip() +
  labs(x = "", y = "Extra penalties (in %) for Muslims and recent immigrants") +
  theme_minimal() +
  theme(legend.position="bottom")

## Save Figure 2
# ggsave("Figure_2.pdf", plot = last_plot(), width = 8, height = 4)

## Generate the plotdata
plotdata <- bind_rows(
  tidy(Mod2_H5) %>% filter(term == "NameMuslim name" | term == "LoRLives in DK since 1 year") %>%
  tidy(Mod2_H6) %>% filter(term == "LoRLives in DK since 1 year") %>% mutate(model = "Mod2_H6", c
  tidy(Mod2_H7) %>% filter(term == "NameMuslim name") %>% mutate(model = "Mod2_H7", condition = "
  tidy(Mod2_H8) %>% filter(term == "LoRLives in DK since 1 year") %>% mutate(model = "Mod2_H8", c
```

17

```r
  tidy(Mod2_H9) %>% filter(term == "NameMuslim name") %>% mutate(model = "Mod2_H9", condition = "
  tidy(Mod3_a) %>% filter(term == "NameMuslim name" | term == "LoRLives in DK since 1 year") %>%
  tidy(Mod3_b) %>% filter(term == "NameMuslim name" | term == "LoRLives in DK since 1 year") %>%
  tidy(Mod3_c) %>% filter(term == "LoRLives in DK since 1 year") %>% mutate(model = "Mod3c", cond
  tidy(Mod3_d) %>% filter(term == "NameMuslim name") %>% mutate(model = "Mod3d", condition = "Fol
  # tidy(Mod3e) %>% filter(term == "NameMuslim name" | term == "LoRLives in DK since 1 year") %>%
  mutate(
    term = gsub("LoR","",term),
    term = gsub("Name","",term),
    min90 = (estimate - qt(0.95, df) * std.error) * 100,
    min95 = (estimate - qt(0.975, df) * std.error) * 100,
    max90 = (estimate + qt(0.95, df) * std.error) * 100,
    max95 = (estimate + qt(0.975, df) * std.error) * 100,
    label_up = round(estimate, digits = 3) * 100,
    estimate = estimate * 100,
    test = test %>% factor() %>% fct_relevel("Pre-registered", "Exploratory"),
    condition = condition %>% factor() %>%
      fct_relevel("Native born or Nordic name (resp.)", "Followed guidelines carefully", "Healthy
                  "Native born or Nordic name (resp.)\n& followed guidelines carefully",
                  "Followed guidelines carefully\n& healthy lifestyle",
                  "Native born or Nordic name (resp.)\n& healthy lifestyle"))
## Plot
ggplot(data = plotdata, aes(y = estimate, x = condition, estimate, shape = term)) +
  geom_hline(yintercept = 0, color = "#901A1E", lty = "dashed") +
  geom_linerange(aes(ymin = min95, ymax = max95), color = "#808080", position = position_dodge(wi
  geom_pointrange(aes(ymin = min90, ymax = max90), fill = "white", position = position_dodge(widt
  scale_shape_manual(name = "", values = c(21, 19)) +
  geom_text(aes(label = label_up), position = position_dodge(width = 0.7), vjust = -1.2, size = 3
  coord_flip() +
  facet_grid(test ~ ., scales = "free", space = "free") +
  labs(x = "", y = "Remaining difference (in %) to native-born or Nordic-named person \nunder var
  theme_bw() +
  theme(panel.grid.minor = element_line(colour="white"),
        legend.box = "vertical",
        legend.background = element_rect(fill=NA, color=NA),
        legend.key        = element_rect(fill =NA, color =NA),
        strip.background = element_rect(fill = "#f1f1f1", color = NA)) +
  theme(legend.position="bottom")

## Save Figure 3
# ggsave("Figure_3.pdf", plot = last_plot(), width = 10, height = 7)
```
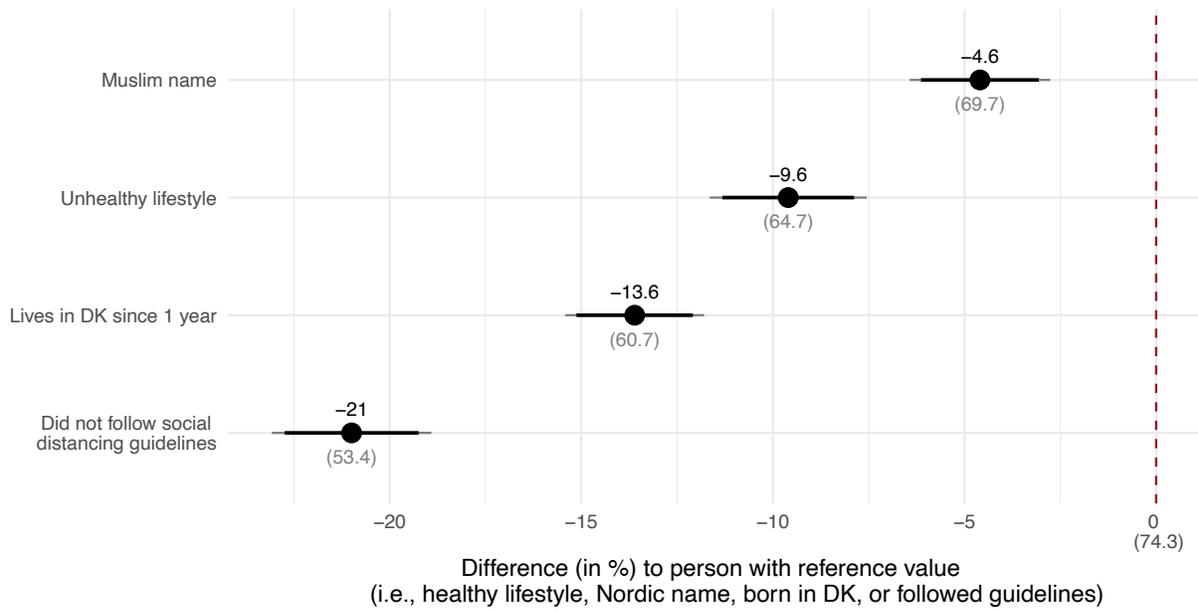
18

Figure 1: Average marginal component effects on who should get vaccinated first
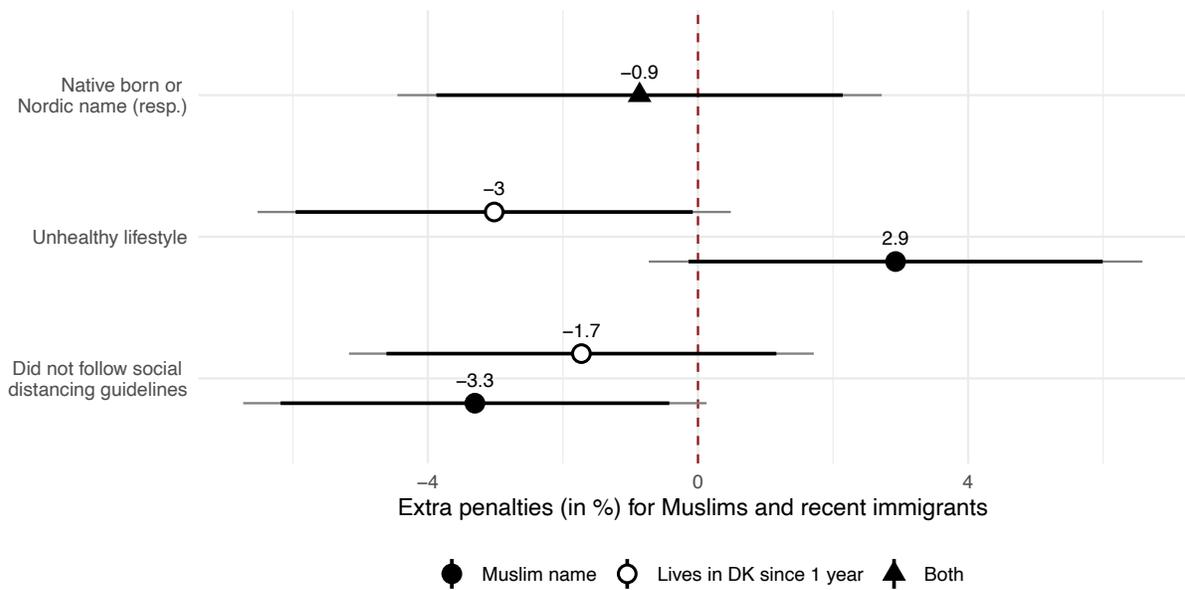

Figure 2: Average marginal component effects on who should get vaccinated first
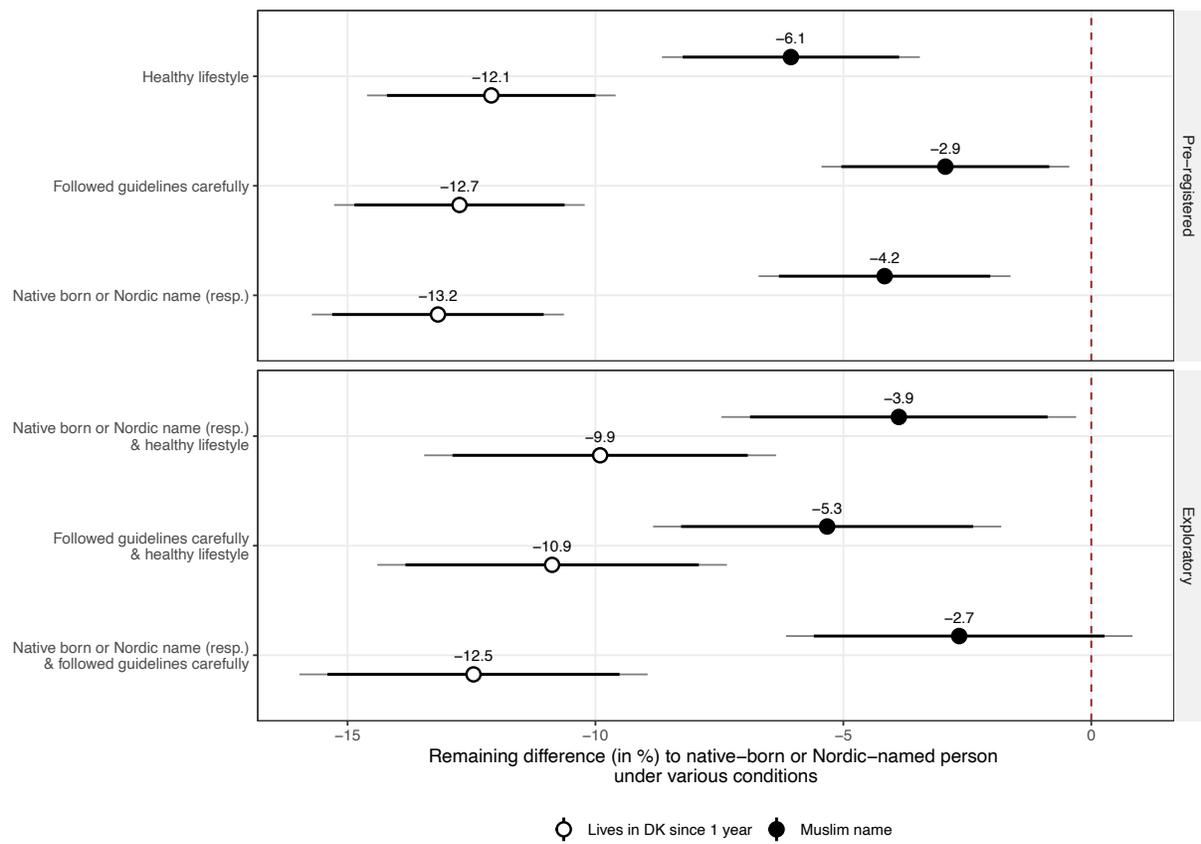
19

Figure 3: Extra penalties for Muslims and recent immigrants

Appendix B: Pre-treatment concerns about the COVID-19 vaccination program

Given the timing of the fieldwork before and after the first person was vaccinated but also with Christmas in between, one can wonder whether concerns regarding the vaccination program were constant across the study period. We can directly assess this question because we asked participants after the introduction to our experiment but before the vignette three questions about their concerns regarding the COVID-19 vaccination program. On a scale running from "Completely disagree (1)" to "Completely agree (5)". Figure 4 shows that overall Danes are very optimistic about the COVID-19 vaccination program. Very few do not want to get vaccinated, are concerned about potential side effects, and many were positive that the majority of the population will have been vaccinated by the end of June already days after the first vaccine became available in Denmark. Most importantly, however, Figure 4 shows hardly any time trend in the answers to these questions.

Another concern is whether the results hold when we exclude those do not want to get vaccinated or are very concerned about side effects. For these people getting vaccinated first is arguably not a good thing. A related argument can be made for those who were during the first week of the vaccination program already optimistic that the majority of the population will be able to get the vaccine in the first half of 2021. For these people, getting vaccinated *first* might be less relevant. Table and table show results of the average marginal component effects and average marginal component interaction effects (cf. Figure 1 and Figure 2) for samples of respondents who do not belong to either of the above three groups. Table replicates all full sample results. Table by and large replicates the full sample results. The average marginal component interaction effect between having a Muslim name and not having followed the social distancing and mask wearing guidelines is of unaltered strength ($\beta_{\text{Reduced sample}} = 0.034$ as compared to $\beta_{\text{Full sample}} = 0.033$) but not (marginally) significant anymore.

Finally, we explore whether there is a time trend in the main findings, by interacting the component effect of having a Muslim name or a recent immigrant status with the (z-standardized) day of the interview. We do not find exploratory evidence of a statistically significant (at conventional levels) change in the effect sizes over time.

```
plotdata <- Vac_data_wide %>%
  mutate(
    ## Day of the interview
    Day = as.Date(ActualSurveyEndTime),
    ## Pre-treatment opinions on vaccine.
    q1_1_resp = case_when( ### Want to get vaccinated.
      q1_1_resp == "1 - Helt enig" ~ 5,
      q1_1_resp == "2" ~ 4,
      q1_1_resp == "3" ~ 3,
      q1_1_resp == "4" ~ 2,
      q1_1_resp == "5 - Helt uenig" ~ 1,
      TRUE ~ as.numeric(NA)),
    q1_2_resp = case_when( ### Afraid of side-effects.
      q1_2_resp == "1 - Helt enig" ~ 5,
      q1_2_resp == "2" ~ 4,
      q1_2_resp == "3" ~ 3,
      q1_2_resp == "4" ~ 2,
      q1_2_resp == "5 - Helt uenig" ~ 1,
      TRUE ~ as.numeric(NA)),
    q1_3_resp = case_when( ### Believe majority will be vaccinated until June.
```

```r
      q1_3_resp == "1 - Helt enig" ~ 5,
      q1_3_resp == "2" ~ 4,
      q1_3_resp == "3" ~ 3,
      q1_3_resp == "4" ~ 2,
      q1_3_resp == "5 - Helt uenig" ~ 1,
      TRUE ~ as.numeric(NA)))


Want_vaccine <- ggplot(data = plotdata, aes(y = q1_1_resp, x = Day)) +
  geom_jitter(aes(size = weight), alpha = 1/10, height = 0.2) +
  geom_hline(yintercept = mean(plotdata$q1_1_resp, na.rm = TRUE),
             lty = "dashed", color = "#901A1E") +
  geom_smooth(aes(weight = weight)) +
  scale_y_continuous(
    breaks = 1:5,
    labels = c("(1) Completely \n disagree", "2", "3", "4", "(5) Completely \n agree")) +
  labs(
    title = "I will get vaccinated, once I am offered a COVID-19 vaccine",
    x = "", y = "") +
  theme_minimal() +
  theme(legend.position = "none", plot.title = element_text(size = 10))

Sideeffects <-ggplot(data = plotdata, aes(y = q1_2_resp, x = Day)) +
  geom_jitter(aes(size = weight), alpha = 1/10, height = 0.2) +
  geom_hline(yintercept = mean(plotdata$q1_2_resp, na.rm = TRUE),
             lty = "dashed", color = "#901A1E") +
  geom_smooth(aes(weight = weight)) +
  scale_y_continuous(
    breaks = 1:5,
    labels = c("(1) Completely \n disagree", "2", "3", "4", "(5) Completely \n agree")) +
  labs(
    title = "I am worried about the side effects of the COVID-19 vaccines",
    x = "", y = "") +
  theme_minimal() +
  theme(legend.position = "none", plot.title = element_text(size = 10))

Before_june <- ggplot(data = plotdata, aes(y = q1_3_resp, x = Day)) +
  geom_jitter(aes(size = weight), alpha = 1/10, height = 0.2) +
  geom_hline(yintercept = mean(plotdata$q1_3_resp, na.rm = TRUE),
             lty = "dashed", color = "#901A1E") +
  geom_smooth(aes(weight = weight)) +
  scale_y_continuous(
    breaks = 1:5,
    labels = c("(1) Completely \n disagree", "2", "3", "4", "(5) Completely \n agree")) +
  labs(
    title = "I expect the majority of the Danish population will be able \n to get a COVID-19 vac
    x = "", y = "") +
  theme_minimal() +
  theme(legend.position = "none", plot.title = element_text(size = 10))
```

```r
ggarrange(Want_vaccine, Sideeffects, Before_june, labels = c("A", "B", "C"), nrow = 3)
```

A I will get vaccinated, once I am offered a COVID−19 vaccine

B I am worried about the side effects of the COVID−19 vaccines

C I expect the majority of the Danish population will be able
to get a COVID-19 vaccination within the
first half of 2021 (that is, end of June)
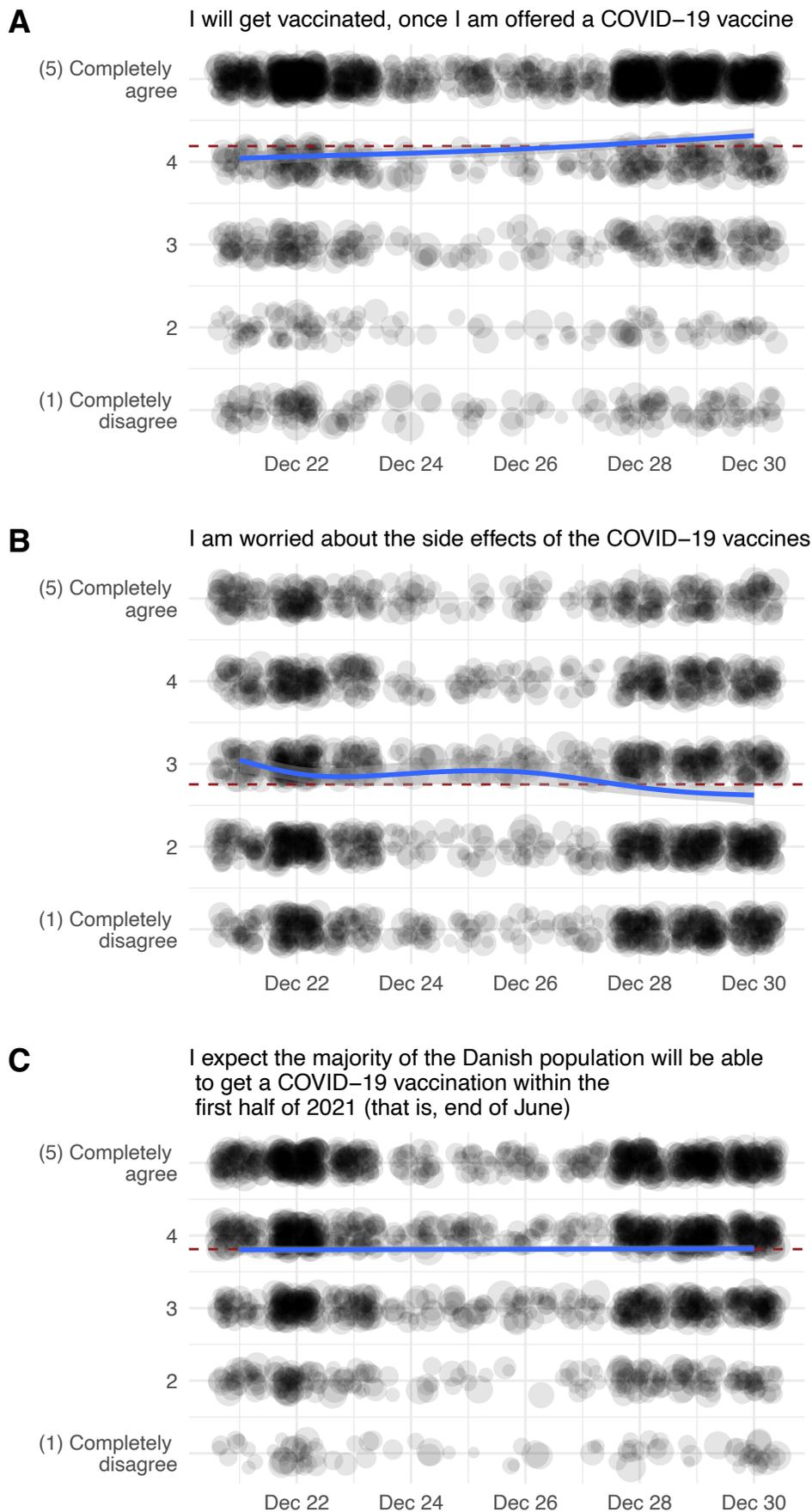
Figure 4: Pre-treatment concerns about the COVID-19 vaccination program

24

```r
#--------------------------
# 1. "Average effects": AMCE
#--------------------------
## Simple OLS
Mod1_a <- lm_robust(
  data = Vac_data_long %>% filter(q1_1_resp > 1),
  formula = Answer ~ LoR + Name + Duty + Health,
  clusters = id, weights = weight)
Mod1_b <- lm_robust(
  data = Vac_data_long %>% filter(q1_2_resp < 5),
  formula = Answer ~ LoR + Name + Duty + Health,
  clusters = id, weights = weight)
Mod1_c <- lm_robust(
  data = Vac_data_long %>% filter(q1_3_resp < 5),
  formula = Answer ~ LoR + Name + Duty + Health,
  clusters = id, weights = weight)
Mod1_d <- lm_robust(
  data = Vac_data_long %>% filter(q1_1_resp > 1 & q1_2_resp < 5 & q1_3_resp < 5),
  formula = Answer ~ LoR + Name + Duty + Health,
  clusters = id, weights = weight)

texreg(
  list(Mod1, Mod1_a, Mod1_b, Mod1_c, Mod1_d),
  include.ci = FALSE, include.rmse = FALSE, digits = 3,
  custom.header = list("Original results" = 1, "Excludes those who" = 2:5),
  custom.col.pos = c(1, 5),
  custom.model.names = c("Full sample", "will not get vaccinated", "are very worried", "are very
  doctype = FALSE, stars = c(0.001, 0.01, 0.05, 0.1), symbol = "+",
  custom.coef.names = c("(Intercept)", "Lives in DK for 1 year", "Muslim name",
                        "Did not follow social distancing guidelines",
                        "Has diabetes because of an unhealthy lifesyle"),
  caption = "Average marginal component effects on who should get vaccinated first, excluding tho
  caption.above = TRUE, sideways = TRUE, use.packages = FALSE, scriptsize = TRUE)

#----------------------------
# 2. "Extra penalties": Figure 2
#----------------------------
Mod2_H5_d <- lm_robust(
  data = Vac_data_long %>% filter(q1_1_resp > 1 & q1_2_resp < 5 & q1_3_resp < 5),
  formula = Answer ~ LoR*Name + Duty + Health,
  clusters = id, weights = weight)
Mod2_H6_d <- lm_robust(
  data = Vac_data_long %>% filter(q1_1_resp > 1 & q1_2_resp < 5 & q1_3_resp < 5),
  formula = Answer ~ LoR*Health + Name + Duty,
  clusters = id, weights = weight)
Mod2_H7_d <- lm_robust(
  data = Vac_data_long %>% filter(q1_1_resp > 1 & q1_2_resp < 5 & q1_3_resp < 5),
  formula = Answer ~ LoR + Name*Health + Duty,
  clusters = id, weights = weight)
```

```
Mod2_H8_d <- lm_robust(
  data = Vac_data_long %>% filter(q1_1_resp > 1 & q1_2_resp < 5 & q1_3_resp < 5),
  formula = Answer ~ LoR*Duty + Name + Health,
  clusters = id, weights = weight)
Mod2_H9_d <- lm_robust(
  data = Vac_data_long %>% filter(q1_1_resp > 1 & q1_2_resp < 5 & q1_3_resp < 5),
  formula = Answer ~ LoR + Name*Duty + Health,
  clusters = id, weights = weight)

texreg(
  list(Mod2_H5_d, Mod2_H6_d, Mod2_H7_d, Mod2_H8_d, Mod2_H9_d),
  include.ci = FALSE, include.rmse = FALSE, digits = 3,
  doctype = FALSE, stars = c(0.001, 0.01, 0.05, 0.1), symbol = "+",
  custom.coef.names = c("(Intercept)", "Lives in DK for 1 year", "Muslim name",
                        "Did not follow social distancing guidelines",
                        "Has diabetes because of an unhealthy lifesyle",
                        "Lives in DK for 1 year * Muslim name",
                        "Lives in DK for 1 year * has diabetes because of an unhealthy lifesyle",
                        "Muslim Name * has diabetes because of an unhealthy lifesyle",
                        "Lives in DK for 1 year * did not follow social distancing guidelines",
                        "Muslim Name * did not follow social distancing guidelines"),
  caption = "Average marginal component interaction effects on who should get vaccinated first, e
  caption.above = TRUE, sideways = TRUE, use.packages = FALSE, scriptsize = TRUE)
```

Table 6: Average marginal component effects on who should get vaccinated first, excluding those who will not get vaccinated, are afraid of the vaccination, or very optimistic about the COVID-19 vaccination program.

	Original results	Excludes those who			
	Full sample	will not get vaccinated	are very worried	are very optimistic	All three
(Intercept)	0.743***	0.745***	0.737***	0.730***	0.729***
	(0.010)	(0.011)	(0.011)	(0.012)	(0.014)
Lives in DK for 1 year	−0.136***	−0.134***	−0.132***	−0.135***	−0.134***
	(0.009)	(0.010)	(0.010)	(0.012)	(0.013)
Muslim name	−0.046***	−0.041***	−0.040***	−0.037**	−0.042**
	(0.009)	(0.010)	(0.010)	(0.012)	(0.013)
Did not follow social distancing guidelines	−0.210***	−0.215***	−0.208***	−0.203***	−0.198***
	(0.011)	(0.011)	(0.012)	(0.014)	(0.016)
Has diabetes because of an unhealthy lifesyle	−0.096***	−0.102***	−0.095***	−0.084***	−0.081***
	(0.010)	(0.011)	(0.012)	(0.013)	(0.014)
R²	0.075	0.076	0.072	0.069	0.067
Adj. R²	0.074	0.076	0.071	0.069	0.066
Num. obs.	15084	13326	12504	9396	7368
N Clusters	2514	2221	2084	1566	1228

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{+}p < 0.1$

Table 7: Average marginal component interaction effects on who should get vaccinated first, excluding those who will not get vaccinated, are afraid of the vaccination, or very optimistic about the COVID-19 vaccination program.

	Model 1	Model 2	Model 3	Model 4	Model 5
(Intercept)	0.725***	0.716***	0.729***	0.723***	0.720***
	(0.016)	(0.015)	(0.016)	(0.015)	(0.016)
Lives in DK for 1 year	−0.127***	−0.109***	−0.134***	−0.122***	−0.134***
	(0.019)	(0.018)	(0.013)	(0.019)	(0.013)
Muslim name	−0.035$^+$	−0.041**	−0.041*	−0.042**	−0.025
	(0.019)	(0.013)	(0.019)	(0.013)	(0.018)
Did not follow social distancing guidelines	−0.198***	−0.198***	−0.198***	−0.186***	−0.181***
	(0.016)	(0.016)	(0.016)	(0.020)	(0.021)
Has diabetes because of an unhealthy lifestyle	−0.081***	−0.056**	−0.081***	−0.081***	−0.081***
	(0.015)	(0.020)	(0.020)	(0.015)	(0.014)
Lives in DK for 1 year * Muslim name	−0.014				
	(0.027)				
Lives in DK for 1 year * has diabetes because of an unhealthy lifesyle		−0.050$^+$			
		(0.026)			
Muslim Name * has diabetes because of an unhealthy lifestyle			−0.000		
			(0.027)		
Lives in DK for 1 year * did not follow social distancing guidelines				−0.025	
				(0.025)	
Muslim Name * did not follow social distancing guidelines					−0.034
					(0.025)
R^2	0.067	0.068	0.067	0.067	0.067
Adj. R^2	0.066	0.067	0.066	0.066	0.067
Num. obs.	7368	7368	7368	7368	7368
N Clusters	1228	1228	1228	1228	1228

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; $^+p < 0.1$

```r
#-----------------------------
# Effect heterogeneity by time
#-----------------------------
Mod_day_a <- lm_robust(
  data = Vac_data_long,
  formula = Answer ~ LoR*Day + Name + Duty + Health +
  Gender + Age + Region + Education + Pers_HH,
  clusters = id, weights = weight)
Mod_day_b <- lm_robust(
  data = Vac_data_long,
  formula = Answer ~ LoR + Name*Day + Duty + Health +
  Gender + Age + Region + Education + Pers_HH,
  clusters = id, weights = weight)

## OLS with controls
texreg(list(Mod_day_a, Mod_day_b),
        include.ci = FALSE, include.rmse = FALSE, digits = 3,
      doctype = FALSE, stars = c(0.001, 0.01, 0.05, 0.1), symbol = "+",
      omit.coef = "(Male)|(Age)|(RegionMidtjylland)|(RegionNordjylland)|(RegionSjælland)|(Region
      custom.coef.names = c("(Intercept)", "Lives in DK for 1 year", "Muslim name",
                      "Did not follow guidelines",
                      "Has an unhealthy lifesyle",
                      "Day of interview",
                      "Day of interview * Lives in DK for 1 year",
                      "Day of interview * Muslim name"),
      custom.gof.rows = list("Control variables" = c("Yes", "Yes")),
      caption = "Average marginal component interaction effects on who should get vaccinated fir
      caption.above = TRUE, scriptsize = TRUE)
```

Table 8: Average marginal component interaction effects on who should get vaccinated first, additional exploratory results

	Model 1	Model 2
(Intercept)	2.398	50.944$^+$
	(26.613)	(26.611)
Lives in DK for 1 year	−0.618	−0.136***
	(51.434)	(0.009)
Muslim name	−0.000	−0.003$^+$
	(0.001)	(0.001)
Did not follow guidelines	−0.046***	−98.036$^+$
	(0.009)	(51.359)
Has an unhealthy lifesyle	−0.210***	−0.210***
	(0.011)	(0.011)
Day of interview	−0.096***	−0.096***
	(0.010)	(0.010)
Day of interview * Lives in DK for 1 year	0.000	
	(0.003)	
Day of interview * Muslim name		0.005$^+$
		(0.003)
Control variables	Yes	Yes
R^2	0.075	0.075
Adj. R^2	0.074	0.074
Num. obs.	15084	15084
N Clusters	2514	2514

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; $^+p < 0.1$

Appendix C: Speeders and lame ducks

While the survey company already excluded the top 2.5 % fastest respondents before data delivery, we state in the pre-registration that we will investigate if our results are robust to the exclusion of speeders. Looking at the response times shows that the opposite phenomenon might actually be a bigger problem. That is, people taking way too much time implying that they took a break during the survey and might thus have forgotten what the study is all about. The median response time is 211 seconds, that is, roughly 4 minutes.

Figure 1 shows response times, either excluding very slow respondents who needed more than 15 minutes or on a log scale. Very slow respondents are a striking pattern. To test the robustness of our findings we thus re-estimate our models based on respondents who took at least two minutes and at most 15. Excluding speeders and lame ducks leaves our results basically unchanged. The only finding that does not replicate is the interaction effect between recent immigration status and having an unhealthy lifestyle; the estimate drops from 3 to 1.7% and turns insignificant. However, we explicitly described this finding as tentative.

```r
# Calculating survey response time in seconds.
Vac_data_wide <- Vac_data_wide %>%
  mutate(
    Responsetime = (ActualSurveyEndTime - ActualSurveyStartTime) %>%
      as.numeric())

# There are some very long response times.
summary(Vac_data_wide$Responsetime)
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      56     163     211     336     284   40733

# Histogram of questionnaire response time, excluding very slow respondents
histo1 <- ggplot(Vac_data_wide %>% filter(Responsetime < 900), aes(x = Responsetime)) +
  geom_histogram(aes(y = stat(count / sum(count))))+
  labs(title = "Histogram of questionnaire response time",
       caption = "X axis is on a log scale",
       x = "Questionnaire response time in seconds (capped at 900 seconds / 15 minutes)",
       y = "Percentage") +
  theme_minimal()

# Histogram of questionnaire response time, log scale
histo2 <- ggplot(Vac_data_wide, aes(x = Responsetime)) +
  geom_histogram(aes(y = stat(count / sum(count))))+
  scale_x_log10() +
  labs(title = "Histogram of questionnaire response time",
       caption = "X axis is on a log scale",
       x = "Questionnaire response time in seconds (log scale)",
       y = "Percentage") +
  theme_minimal()

ggarrange(histo1, histo2, labels = c("A", "B"), nrow = 2)
```

Min. 1st Qu. Median Mean 3rd Qu. Max. 56 163 211 336 284 40733

A Histogram of questionnaire response time

Questionnaire response time in seconds (capped at 900 seconds / 15 minutes)

X axis is on a log scale

B Histogram of questionnaire response time

Questionnaire response time in seconds (log scale)
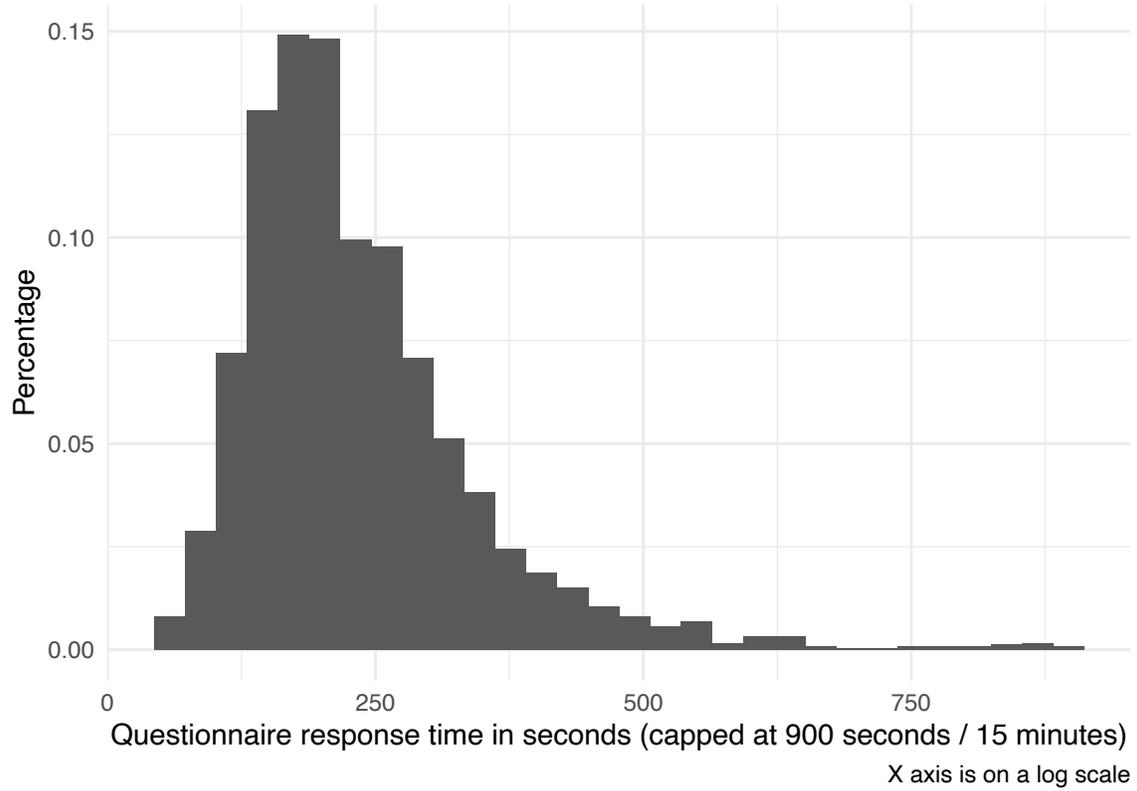
X axis is on a log scale

Figure 5: Histogram of questionnaire response times

Table 9: Average marginal component effects on who should get vaccinated first, excluding those who took less than two and more than fifteen minutes

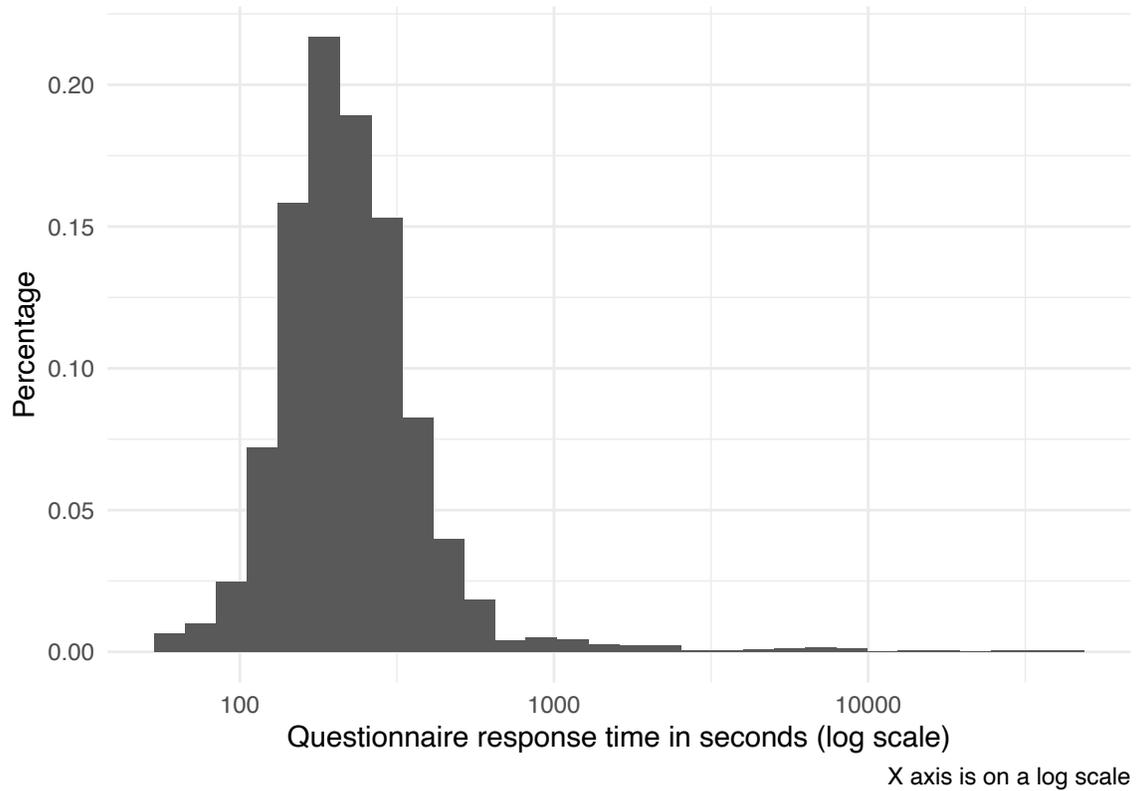|	Full sample	Sample without speeters and lame ducks
(Intercept)	0.743***	0.743***
	(0.010)	(0.010)
Lives in DK for 1 year	−0.136***	−0.139***
	(0.009)	(0.010)
Muslim name	−0.046***	−0.038***
	(0.009)	(0.010)
Did not follow social distancing guidelines	−0.210***	−0.214***
	(0.011)	(0.011)
Has diabetes because of an unhealthy lifesyle	−0.096***	−0.095***
	(0.010)	(0.011)
R^2	0.075	0.076
Adj. R^2	0.074	0.076
Num. obs.	15084	13590
N Clusters	2514	2265

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; +$p < 0.1$

```r
# Re-estimate analysis excluding 5 % fastest respondents
Mod1_speedo <- lm_robust(
  data = Vac_data_long %>% filter(Responsetime > 120 & Responsetime < 900),
  formula = Answer ~ LoR + Name + Duty + Health,
  clusters = id, weights = weight)

texreg(
  list(Mod1, Mod1_speedo),
  include.ci = FALSE, include.rmse = FALSE, digits = 3,
  custom.model.names = c("Full sample", "Sample without speeters and lame ducks"),
  doctype = FALSE, stars = c(0.001, 0.01, 0.05, 0.1), symbol = "+",
  custom.coef.names = c("(Intercept)", "Lives in DK for 1 year", "Muslim name",
                        "Did not follow social distancing guidelines",
                        "Has diabetes because of an unhealthy lifesyle"),
  caption = "Average marginal component effects on who should get vaccinated first, excluding tho
  caption.above = TRUE, scriptsize = TRUE)
```

```r
#------------------------------
# 2. "Extra penalties": Figure 2
#------------------------------
Mod2_H5_speedo <- lm_robust(
  data = Vac_data_long %>% filter(Responsetime > 120 & Responsetime < 900),
  formula = Answer ~ LoR*Name + Duty + Health,
  clusters = id, weights = weight)
Mod2_H6_speedo <- lm_robust(
  data = Vac_data_long %>% filter(Responsetime > 120 & Responsetime < 900),
  formula = Answer ~ LoR*Health + Name + Duty,
  clusters = id, weights = weight)
Mod2_H7_speedo <- lm_robust(
  data = Vac_data_long %>% filter(Responsetime > 120 & Responsetime < 900),
  formula = Answer ~ LoR + Name*Health + Duty,
  clusters = id, weights = weight)
Mod2_H8_speedo <- lm_robust(
  data = Vac_data_long %>% filter(Responsetime > 120 & Responsetime < 900),
  formula = Answer ~ LoR*Duty + Name + Health,
  clusters = id, weights = weight)
Mod2_H9_speedo <- lm_robust(
  data = Vac_data_long %>% filter(Responsetime > 120 & Responsetime < 900),
  formula = Answer ~ LoR + Name*Duty + Health,
  clusters = id, weights = weight)

texreg(
  list(Mod2_H5_speedo, Mod2_H6_speedo, Mod2_H7_speedo, Mod2_H8_speedo, Mod2_H9_speedo),
  include.ci = FALSE, include.rmse = FALSE, digits = 3,
  doctype = FALSE, stars = c(0.001, 0.01, 0.05, 0.1), symbol = "+",
  custom.coef.names = c("(Intercept)", "Lives in DK for 1 year", "Muslim name",
                        "Did not follow social distancing guidelines",
                        "Has diabetes because of an unhealthy lifesyle",
                        "Lives in DK for 1 year * Muslim name",
                        "Lives in DK for 1 year * has diabetes because of an unhealthy lifesyle",
                        "Muslim Name * has diabetes because of an unhealthy lifesyle",
                        "Lives in DK for 1 year * did not follow social distancing guidelines",
                        "Muslim Name * did not follow social distancing guidelines"),
  caption = "Average marginal component interaction effects on who should get vaccinated first, e
  caption.above = TRUE, sideways = TRUE, use.packages = FALSE, scriptsize = TRUE)
```

Table 10: Average marginal component interaction effects on who should get vaccinated first, excluding those who took less than two and more than fifteen minutes

	Model 1	Model 2	Model 3	Model 4	Model 5
(Intercept)	0.743***	0.739***	0.750***	0.738***	0.733***
	(0.011)	(0.011)	(0.012)	(0.011)	(0.011)
Lives in DK for 1 year	−0.138***	−0.130***	−0.139***	−0.129***	−0.139***
	(0.014)	(0.014)	(0.010)	(0.014)	(0.010)
Muslim name	−0.037**	−0.038***	−0.051***	−0.038***	−0.018
	(0.014)	(0.010)	(0.014)	(0.010)	(0.013)
Did not follow social distancing guidelines	−0.214***	−0.214***	−0.214***	−0.205***	−0.194***
	(0.011)	(0.011)	(0.011)	(0.015)	(0.015)
Has diabetes because of an unhealthy lifesyle	−0.095***	−0.086***	−0.108***	−0.095***	−0.095***
	(0.011)	(0.014)	(0.015)	(0.011)	(0.011)
Lives in DK for 1 year * Muslim name	−0.002				
	(0.019)				
Lives in DK for 1 year * has diabetes because of an unhealthy lifestyle		−0.017			
		(0.019)			
Muslim Name * has diabetes because of an unhealthy lifestyle			0.026		
			(0.020)		
Lives in DK for 1 year * did not follow social distancing guidelines				−0.020	
				(0.019)	
Muslim Name * did not follow social distancing guidelines					−0.040*
					(0.018)
R²	0.076	0.077	0.077	0.077	0.077
Adj. R²	0.076	0.076	0.076	0.076	0.077
Num. obs.	13590	13590	13590	13590	13590
N Clusters	2265	2265	2265	2265	2265

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; +$p < 0.1$

Appendix D: Balance test

Although we used block randomization to ensure proper and orthogonal randomization of the four treatments, it is still good practice to illustrate that the randomization was successful. Tables XYZ below show that the randomization of all four treatments seems to have been successful given that all covariates are balanced across the treatment conditions.

```r
## Data prep
Descr_data <- Vac_data_long %>%
  mutate(
    Pers_HH = case_when( ### Number of persons in the household, z-standardized
      bagg4 == "1 person" ~ 1,
      bagg4 == "2 personer" ~ 2,
      bagg4 == "3 personer" ~ 3,
      bagg4 == "4 personer" ~ 4,
      bagg4 == "5 personer" ~ 5,
      bagg4 == "6 personer eller derover" ~ 6) %>% as.numeric())

## Muslim/Nordic Name
Descr_data %>%
  select(Name, Gender, Alder, Region, Education, Pers_HH) %>%
  tbl_summary(
    by = Name,
    statistic = list(all_continuous() ~ "{mean} ({sd})",
                     all_categorical() ~ "{p}% {n}")) %>%
  as_kable_extra()
```

Characteristic	Danish/Nordic name, N = 7,530	Muslim name, N = 7,554
Gender		
Female	51% 3,865	50% 3,767
Male	49% 3,665	50% 3,787
Alder	50 (17)	51 (17)
Region		
Hovedstaden	31% 2,340	31% 2,322
Midtjylland	26% 1,992	27% 2,004
Nordjylland	9.5% 712	8.7% 656
Sjælland	12% 913	12% 929
Syddanmark	21% 1,573	22% 1,643
Education		
Primary	10% 772	9.7% 734
Secondary	46% 3,431	45% 3,403
Tertiary	44% 3,327	45% 3,417
Pers_HH		
1	36% 2,695	35% 2,657
2	50% 3,802	51% 3,842
3	8.8% 664	8.8% 668
4	4.1% 306	4.1% 312
5	0.7% 51	0.8% 57
6	0.2% 12	0.2% 18

[1] % n; Mean (SD)

36

```
## Immigrant status
Descr_data %>%
  select(LoR, Gender, Alder, Region, Education, Pers_HH) %>%
  tbl_summary(
    by = LoR,
    statistic = list(all_continuous() ~ "{mean} ({sd})",
                     all_categorical() ~ "{p}% {n}"))%>%
  as_kable_extra()
```

Characteristic	Born in DK, N = 7,534	Lives in DK since 1 year, N = 7,550
Gender		
Female	51% 3,809	51% 3,823
Male	49% 3,725	49% 3,727
Alder	50 (17)	50 (18)
Region		
Hovedstaden	31% 2,366	30% 2,296
Midtjylland	26% 1,957	27% 2,039
Nordjylland	9.0% 678	9.1% 690
Sjælland	12% 913	12% 929
Syddanmark	22% 1,620	21% 1,596
Education		
Primary	10% 764	9.8% 742
Secondary	46% 3,478	44% 3,356
Tertiary	44% 3,292	46% 3,452
Pers_HH		
1	35% 2,610	36% 2,742
2	51% 3,877	50% 3,767
3	8.5% 643	9.1% 689
4	4.4% 333	3.8% 285
5	0.7% 56	0.7% 52
6	0.2% 15	0.2% 15

[1] % n; Mean (SD)

```
## Social distancing guidelines
Descr_data %>%
  select(Duty, Gender, Alder, Region, Education, Pers_HH) %>%
  tbl_summary(
    by = Duty,
    statistic = list(all_continuous() ~ "{mean} ({sd})",
                     all_categorical() ~ "{p}% {n}"))%>%
  as_kable_extra()
```

Characteristic	Followed guidelines carefully, N = 7,543	Did not follow guidelines, N = 7,541
Gender		
Female	51% 3,861	50% 3,771
Male	49% 3,682	50% 3,770
Alder	51 (18)	50 (17)
Region		
Hovedstaden	30% 2,298	31% 2,364
Midtjylland	27% 2,036	26% 1,960
Nordjylland	9.1% 684	9.1% 684
Sjælland	12% 917	12% 925
Syddanmark	21% 1,608	21% 1,608
Education		
Primary	10% 758	9.9% 748
Secondary	45% 3,416	45% 3,418
Tertiary	45% 3,369	45% 3,375
Pers_HH		
1	35% 2,662	36% 2,690
2	51% 3,823	51% 3,821
3	9.0% 680	8.6% 652
4	4.1% 311	4.1% 307
5	0.7% 56	0.7% 52
6	0.1% 11	0.3% 19

[1] % n; Mean (SD)

```r
## Healthy lifestyle
Descr_data %>%
  select(Health, Gender, Alder, Region, Education, Pers_HH) %>%
  tbl_summary(
    by = Health,
    statistic = list(all_continuous() ~ "{mean} ({sd})",
                     all_categorical() ~ "{p}% {n}"))%>%
  as_kable_extra()
```

Characteristic	Healthy lifestyle, N = 7,539	Unhealthy lifestyle, N = 7,545
Gender		
Female	50% 3,794	51% 3,838
Male	50% 3,745	49% 3,707
Alder	50 (17)	51 (17)
Region		
Hovedstaden	31% 2,326	31% 2,336
Midtjylland	26% 1,976	27% 2,020
Nordjylland	9.5% 715	8.7% 653
Sjælland	12% 935	12% 907
Syddanmark	21% 1,587	22% 1,629
Education		
Primary	9.5% 719	10% 787
Secondary	46% 3,459	45% 3,375
Tertiary	45% 3,361	45% 3,383
Pers_HH		
1	35% 2,653	36% 2,699
2	51% 3,855	50% 3,789
3	8.6% 648	9.1% 684
4	4.3% 323	3.9% 295
5	0.7% 50	0.8% 58
6	0.1% 10	0.3% 20

[1] % n; Mean (SD)

Appendix E: Exploratory analyses of effect heterogeneity by gender, education, age

Prior research shows that men, the less educated and older respondents are more xenophobic and racist. Against this background we explore here whether our main findings of racist-driven and reciprocity motivated healthcare chauvinism are more pronounced among these populations. The findings suggest that men penalize Muslims more than women, but women penalize recent immigrants more. Thus with regard to gender the evidence is rather mixed. We do not find any differences with respect to age. However, racist-driven but not reciprocity-motivated healthcare chauvinism is significantly more pronounced among the less educated.

```
#----------
# 1. Gender
#----------
Mod_gender_a <- lm_robust(
  data = Vac_data_long,
  formula = Answer ~ LoR*Gender + Name + Duty + Health +
  Age + Region + Education + Pers_HH + Day,
  clusters = id, weights = weight)
Mod_gender_b <- lm_robust(
  data = Vac_data_long,
  formula = Answer ~ LoR + Name*Gender + Duty + Health +
  Age + Region + Education + Pers_HH + Day,
  clusters = id, weights = weight)
```

Table 11: Average marginal component interaction effects on who should get vaccinated first, additional exploratory results

	Model 1	Model 2
(Intercept)	2.194	1.436
	(6.573)	(6.648)
Lives in DK for 1 year	−0.157***	−0.136***
	(0.013)	(0.009)
Muslim name	−0.016+	0.029**
	(0.009)	(0.010)
Did not follow guidelines	−0.046***	−0.020
	(0.009)	(0.013)
Has an unhealthy lifesyle	−0.210***	−0.210***
	(0.011)	(0.011)
Male	−0.096***	−0.096***
	(0.010)	(0.010)
Male * Lives in DK for 1 year	0.040*	
	(0.018)	
Male * Muslim name		−0.051**
		(0.019)
Control variables	Yes	Yes
R^2	0.075	0.075
Adj. R^2	0.074	0.074
Num. obs.	15084	15084
N Clusters	2514	2514

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; +$p < 0.1$

```
## OLS with controls
texreg(list(Mod_gender_a, Mod_gender_b),
        include.ci = FALSE, include.rmse = FALSE, digits = 3,
      doctype = FALSE, stars = c(0.001, 0.01, 0.05, 0.1), symbol = "+",
      omit.coef = "(Age)|(RegionMidtjylland)|(RegionNordjylland)|(RegionSjælland)|(RegionSyddanm
      custom.coef.names = c("(Intercept)", "Lives in DK for 1 year", "Muslim name",
                    "Did not follow guidelines",
                    "Has an unhealthy lifesyle",
                    "Male",
                    "Male * Lives in DK for 1 year",
                    "Male * Muslim name"),
      custom.gof.rows = list("Control variables" = c("Yes", "Yes")),
      caption = "Average marginal component interaction effects on who should get vaccinated fir
      caption.above = TRUE, scriptsize = TRUE)
```

```r
#-------
# 2. Age
#-------
Mod_age_a <- lm_robust(
  data = Vac_data_long,
  formula = Answer ~ LoR*Age + Name + Duty + Health +
  Gender + Region + Education + Pers_HH + Day,
  clusters = id, weights = weight)
Mod_age_b <- lm_robust(
  data = Vac_data_long,
  formula = Answer ~ LoR + Name*Age + Duty + Health +
  Gender + Region + Education + Pers_HH + Day,
  clusters = id, weights = weight)

## OLS with controls
texreg(list(Mod_age_a, Mod_age_b),
         include.ci = FALSE, include.rmse = FALSE, digits = 3,
       doctype = FALSE, stars = c(0.001, 0.01, 0.05, 0.1), symbol = "+",
       omit.coef = "(Male)|(RegionMidtjylland)|(RegionNordjylland)|(RegionSjælland)|(RegionSyddan
       custom.coef.names = c("(Intercept)", "Lives in DK for 1 year", "Muslim name",
                       "Did not follow guidelines",
                       "Has an unhealthy lifesyle",
                       "Age",
                       "Age * Lives in DK for 1 year",
                       "Age * Muslim name"),
       custom.gof.rows = list("Control variables" = c("Yes", "Yes")),
       caption = "Average marginal component interaction effects on who should get vaccinated fir
       caption.above = TRUE, scriptsize = TRUE)
```

Table 12: Average marginal component interaction effects on who should get vaccinated first, additional exploratory results

	Model 1	Model 2
(Intercept)	2.264	2.331
	(6.577)	(6.595)
Lives in DK for 1 year	−0.136***	−0.136***
	(0.009)	(0.009)
Muslim name	−0.005	0.005
	(0.005)	(0.005)
Did not follow guidelines	−0.046***	−0.046***
	(0.009)	(0.009)
Has an unhealthy lifesyle	−0.210***	−0.210***
	(0.011)	(0.011)
Age	−0.096***	−0.096***
	(0.010)	(0.010)
Age * Lives in DK for 1 year	0.005	
	(0.009)	
Age * Muslim name		−0.014
		(0.009)
Control variables	Yes	Yes
R^2	0.075	0.075
Adj. R^2	0.074	0.074
Num. obs.	15084	15084
N Clusters	2514	2514

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; +$p < 0.1$

```r
#-------------
# 3. Education
#-------------
Mod_educ_a <- lm_robust(
  data = Vac_data_long,
  formula = Answer ~ LoR*Education + Name + Duty + Health +
  Gender + Age + Region + Pers_HH + Day,
  clusters = id, weights = weight)
Mod_educ_b <- lm_robust(
  data = Vac_data_long,
  formula = Answer ~ LoR + Name*Education + Duty + Health +
  Gender + Age + Region + Pers_HH + Day,
  clusters = id, weights = weight)

## OLS with controls
texreg(list(Mod_educ_a, Mod_educ_b),
       include.ci = FALSE, include.rmse = FALSE, digits = 3,
       doctype = FALSE, stars = c(0.001, 0.01, 0.05, 0.1), symbol = "+",
       omit.coef = "(Male)|(Age)|(RegionMidtjylland)|(RegionNordjylland)|(RegionSjælland)|(Region
       custom.coef.names = c("(Intercept)", "Lives in DK for 1 year", "Muslim name",
                             "Did not follow guidelines",
                             "Has an unhealthy lifesyle",
                             "Secondary education", "Tertiary education",
                             "Secondary education * Lives in DK for 1 year",
                             "Tertiary education * Lives in DK for 1 year",
                             "Secondary education * Muslim name",
                             "Tertiary education * Muslim name"),
       custom.gof.rows = list("Control variables" = c("Yes", "Yes")),
       caption = "Average marginal component interaction effects on who should get vaccinated fir
       caption.above = TRUE, scriptsize = TRUE)
```

Table 13: Average marginal component interaction effects on who should get vaccinated first, additional exploratory results

	Model 1	Model 2
(Intercept)	1.906	1.883
	(6.612)	(6.629)
Lives in DK for 1 year	−0.138***	−0.136***
	(0.027)	(0.009)
Muslim name	0.003	0.001
	(0.015)	(0.016)
Did not follow guidelines	−0.006	−0.030+
	(0.015)	(0.016)
Has an unhealthy lifesyle	−0.046***	−0.065*
	(0.009)	(0.028)
Secondary education	−0.210***	−0.210***
	(0.011)	(0.011)
Tertiary education	−0.096***	−0.096***
	(0.010)	(0.010)
Secondary education * Lives in DK for 1 year	−0.008	
	(0.030)	
Tertiary education * Lives in DK for 1 year	0.016	
	(0.030)	
Secondary education * Muslim name		−0.004
		(0.031)
Tertiary education * Muslim name		0.064*
		(0.031)
Control variables	Yes	Yes
R^2	0.075	0.076
Adj. R^2	0.074	0.075
Num. obs.	15084	15084
N Clusters	2514	2514

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; +$p < 0.1$

Appendix F: Outlier analysis

Our pre-registration states that we will perform an outlier analysis. In the aftermath this seems unnecessary given that all treatments and outcomes are binary. However, since we stated it, we present the code that tests for outliers here. The results are obviously not alarming. However, we refrain from printing the actual figures because they tremendously increase the filesize of the pdf.

```r
#--------------------------
# 1. "Average effects": AMCE
#--------------------------
dfbetasPlots(
  lm(data = Vac_data_long,
     formula = Answer ~ LoR + Name + Duty + Health,
     weights = weight))
```

```r
#------------------------------
# 2. "Extra penalties": Figure 2
#------------------------------
dfbetasPlots(
  lm(data = Vac_data_long,
     formula = Answer ~ LoR*Name + Duty + Health,
     clusters = id, weights = weight))

dfbetasPlots(
  lm(data = Vac_data_long,
     formula = Answer ~ LoR*Health + Name + Duty,
     clusters = id, weights = weight))

dfbetasPlots(
  lm(data = Vac_data_long,
     formula = Answer ~ LoR + Name*Health + Duty,
     clusters = id, weights = weight))

dfbetasPlots(
  lm(data = Vac_data_long,
     formula = Answer ~ LoR*Duty + Name + Health,
     clusters = id, weights = weight))

dfbetasPlots(
  lm(data = Vac_data_long,
     formula = Answer ~ LoR + Name*Duty + Health,
     clusters = id, weights = weight))
```