European Economic Review 150 (2022) 104293

Contents lists available at ScienceDirect

European Economic Review

journal homepage: www.elsevier.com/locate/eer

The impact of COVID-19 vaccination for mental well-being

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ARTICLE INFO

JEL Classification:
I12
I31

Keywords:
Covid-19
Mental well-being
Vaccination
Propensity score matching

ABSTRACT

We examine the impact of vaccination against Covid-19 for mental health. Our estimates suggest that vaccination led to a significant and substantive improvement in mental health. These positive impacts were however concentrated on those most at risk of hospitalisation and death from Covid-19, namely older and clinically vulnerable groups. Our proposed explanation is that in the absence of vaccination, anxiety about contracting COVID-19 has a deleterious impact on the mental health of this cohort. On the other hand, vaccination was much less impactful for the mental health of those least at risk from Covid-19. This may help to explain vaccine hesitancy amongst young people. For this group, a lack of uptake may be principally due to a lack of perceived benefits (and indeed perceived costs) for their own well-being as opposed to vaccine hesitancy.

1. Introduction

There is an extensive literature documenting the economic impacts of the COVID-19 pandemic. To fully appreciate the consequences of this pandemic for human welfare we need to assess its impact on our mental health as well as economic well-being. With this in mind, a nascent literature is beginning to carefully detail the consequences of the pandemic for people's mental health. A consistent finding in the emerging literature on this topic is that the Covid-19 pandemic, particularly the social distancing restrictions, is associated with a substantive rise in psychological distress (see Banks et al., 2021 for a recent review of this literature). To date, the main approach to quantifying the mental health burden in this literature is to rely on surveys which ask individuals to report their mental well-being at various stages during the pandemic. A significant number of these studies have similar measures of well-being pre-pandemic allowing people to track changes in mental health over time.

While this research suggests that the impact of the pandemic for mental health can be substantive, these effects are not uniformly distributed. As an illustration, using data from Understanding Society, Daly et al. (2020) reported that 18–34 year-olds were disproportionately impacted, relative to other groups. Further studies have reported that women, ethnic minorities and those faced with financial insecurity are also disproportionately negatively impacted (Anaya et al., 2021; Banks and Xu, 2020:2021; Cheng et al., 2021; Daly et al., 2020; Etheridge and Spantig, 2020; Giovanis and Ozdamar, 2020; Niedzwiedz et al., 2021; Proto and Quintana--Domeque, 2021; Schmidtke et al., 2021; Shen and Bartram, 2021; Swaziek and Wozniak, 2020; Zamarro and Prados, 2021).

Some potential limitations with this existing literature is that even when data is available before the pandemic, these studies are not able to precisely identify an appropriate counterfactual. This can be important as, for example, some mental health measures have been

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[1] We are grateful to the editor in charge of this submission and an anonymous reviewer for helpful comments and suggestions. The usual disclaimer applies.

https://doi.org/10.1016/j.euroecorev.2022.104293
Received 16 November 2021; Received in revised form 14 September 2022; Accepted 14 September 2022
Available online 27 September 2022

trending downwards prior to the pandemic and therefore before and-after comparisons may overstate the mental health burden (Banks et al., 2021). Additionally, there are seasonal patterns to reported mental health measures, meaning that any reported difference in mental health pre-and post-pandemic may be partly confounded with seasonal trends. A further consideration when assessing the existing literature is the relevant interpretation. By comparing the self-reported well-being from individuals surveyed during certain time periods, the estimated disutility associated with the pandemic will be sensitive to the dates selected. The question here is when does the pandemic start/end and what constitutes the reference time period.

We offer an alternative way of quantifying the consequences of the pandemic for mental health. Specifically, we look to estimate the impact of receiving a Covid-19 vaccine for mental health as captured by the General Health Questionnaire (GHQ). Our central hypothesis is that vaccination will largely remove health related anxiety for vaccinated adults as they have been shown to be remarkably effective in reducing illness and death. For instance, estimates at the time individuals in our household survey were vaccinated suggested an upwards of 90% reduction in the probability of hospitalisation and death.[2] While the pandemic may still negatively impact the mental health of people through other channels such as social distancing, health related anxiety (at least as applied to oneself) should we suggest be largely eliminated once vaccinated. Accordingly, for the 'treated', our estimates of the impact of vaccination for mental health can be seen as a reasonable lower-bound estimate of health-related anxiety associated with the pandemic itself. These estimates should supplement the emerging body of work quantifying the mental health impact of lockdowns and other less restrictive interventions such as social distancing guidelines aimed at minimising the spread of Covid-19.

In determining the impact of vaccination for mental health, we compare the mental health of individuals who have received the Covid-19 vaccine with the mental health of those who have not. Here we take advantage of wave 7 and 8 of Covid-19 surveys by the UK Household Longitudinal Study as these surveys record a measure of people's mental health as captured by the General Health Questionnaire, their vaccine status and also their willingness to take a vaccine. At the time these surveys were undertaken, about 43% of the sample population had taken at least one dose of the vaccine. We are able to take advantage of significant variation in the actual number as well as characteristics of people who have taken the vaccine in these surveys. One of the reasons for such variation is that there was significant spatial variation in the uptake of vaccines in the UK, mainly for logistical reasons. Simply put, some local authorities were in a better position to distribute vaccines than others. Second, the interview dates are randomised across each wave.

One potential problem with this direct comparison approach is that both groups labelled hereafter for ease of writing as treatment (taken at least one dose of vaccine) and control group (have not taken the vaccine) may differ in ways that matter when it comes to measuring the impact of the vaccine for mental health. For example, vaccines were distributed based on clinical need with clinical need being principally determined by age and the presence of underlying health conditions. Therefore, a raw estimate of the difference in mental health between both groups may confound the beneficial impact of the vaccine with other characteristics such as age and health.

Another relevant consideration is that while individuals could not choose to take a vaccine as availability was based on clinical need, they could *choose* not to take one. It is possible that individuals who choose not to take a vaccine may differ in relevant background characteristics which could also be related with mental health. This is however less likely to be an issue in the UK than elsewhere as general acceptance of the vaccine is high as compared to similar European countries. In short, the unbalanced distributions of characteristics between the two groups may create a problem with selection bias and, in turn, a biased estimate of the average treatment effect for the treated.

Our approach to dealing with this potential bias is to employ various matching techniques, such as covariate matching (CVM), propensity score matching (PSM) and entropy balancing. The basic idea behind matching approaches is to find in a large group of individuals who are not exposed to the treatment, those individuals who are most similar to treated units in all relevant pre-treatment characteristics. In practice it involves reweighting or simply discarding units in order to ensure that the treatment and control group have similar distributions of characteristics so that the treatment variable becomes closer to being independent of the background characteristics (Hainmueller 2012). By helping to ensure that both groups have equal distributions of characteristics much like what would be observed under random assignment, matching can lead to more reliable estimates of 'treatment' effects in the presence of non-random assignment. In this case, after matching, those in the control group have a similar probability of being offered the vaccine as those observed in the treatment group. This is facilitated by matching on the basis of observed characteristics such as age and health status, factors we know will predict the likelihood of being offered a vaccine.

Fortunately, in our dataset, we also have a variable which asks individuals if they are willing to take a vaccine. This means we can match individuals not only when it comes to their individual characteristics which predict the likelihood of them being offered a vaccine but also their willingness to take one.[3] In such a scenario we argue that the differences between both groups after matching can be seen as an unbiased estimate of the average treatment effect (ATT) for the treated (people who have taken the vaccine) because the treatment group does not on average differ systematically from our matched control group consisting of those who have not taken the vaccine.

Our main findings suggest that vaccination led to a significant and substantive improvement in mental health. This is principally evident, however, for those most at health risk from Covid-19, namely older demographics and/or those with underlying health

[2] More recent estimates of vaccine effectiveness suggest a more nuanced picture. For example, while still effective (albeit less so) in preventing hospitalisation and in particular death they appear to be much less effective at preventing infection and transmission (see: COVID-19 vaccine surveillance report Week 35 and COVID-19 vaccine surveillance report Week 24 for a more updated picture).

[3] In our sample, around 7.5% of the respondents were unwilling to take the vaccine. For unknown reasons 5% of the vaccinated respondents indicated that they were not willing to take vaccine. Our results remain qualitatively the same if we drop these observations.

conditions. In contrast to older demographics, the estimated benefits of vaccination for younger cohorts in terms of their own mental well-being is significantly less. This we posit may be an important factor underpinning comparatively lower rates of vaccine uptake amongst young adults. For this demographic, lower rates of vaccine uptake could at least partly be the result of a rational calculation of what they perceive as the benefits for their own well-being versus the actual costs (e.g. time and risks however small of serious side effects) of vaccination.

2. Dataset and key variables

We employ data from the UK Household Longitudinal Study (UKHLS) also known as Understanding Society. The UKHLS is a household panel that captures, amongst other things, information from adults about their economic and social circumstances, socio-demographics and mental health. Our key outcome variable of mental health contained in this survey dataset is the 12-item version of the General Health Questionnaire (GHQ-12). This 12-item scale is designed to assess somatic symptoms, anxiety and insomnia, social dysfunction, and general happiness (see Table A1 in appendix for a list of all question items). It is possibly the most commonly used measure of subjective well-being in the literature (Jackson 2007). The GHQ offers an advantage over single question measures of subjective well-being, such as happiness and life satisfaction as it is based on responses to 12 separate questions. Each of the 12 items is scored on a four-point scale. The overall GHQ score can take values from 0 to 36, with 36 representing the lowest level of psychological well-being. For ease of interpretation, we reversed the overall score so that a value of 36 represents the highest level and going forward we refer to this variable simply as mental health or mental well-being.

Beginning in April 2020, participants of the UKHLS were asked to complete a short online survey on the impact of the COVID-19 pandemic (see University of Essex Institute for Social and Economic Research 2021, Understanding Society Covid-19 Study; University of Essex Institute for Social and Economic Research 2021, Understanding Society Covid-1: User Guide). The survey consists of all eligible consented individuals aged 16 years and over in eligible households. The survey was undertaken monthly between April-July 2020 and then every two months thereafter. Beginning in Wave 7 of these monthly surveys, respondents were questioned in relation to whether they had taken a vaccine for covid-19 as well as their willingness to take one in the absence of vaccination. In the analysis that follows we focus on wave 7 and 8[4] of these special Covid-19 surveys given the availability of information pertaining to vaccine status, vaccine willingness and whether people were classified as clinically vulnerable to Covid-19. We discuss the structure of these variables in the following section.

2.1. Key variables

The National Health Service (NHS) in the UK created a two-level priority list classifying those most at risk from serious illness if they are infected by COVID-19. People in the first list were deemed clinically extremely vulnerable[5] to Covid-19 and individuals belonging to this category included, amongst others, those with serious health conditions such as receiving cancer treatment, those who have a lung condition such as cystic fibrosis, severe asthma or COPD, or a compromised immune system. The second 'priority' list for vaccination consisted of individuals deemed at high risk, at least relative to the rest of the population. This included care home residents and care home workers, frontline health and social care workers, those with underlying health conditions that put them at greater risk (e.g. diabetes) and people aged 50 and over. We used a binary indicator to indicate whether individuals belong to one of these priority lists and thus at comparatively higher risk from hospitalisation and death from Covid-19. We label this variable as 'clinically vulnerable'.

As noted above, health and social care workers were placed in a priority list for vaccination. Other 'key workers' were not placed in the priority list but the UKHLS does capture whether individuals are classified as key workers during the pandemic. This included people working in Education and childcare, Key public services, Local and national government, Food and other necessary goods, Public safety and national security, Transport, Utilities, Communications and financial services. We derived a binary indicator classified whether individuals work in one of these employment categories which we label as key worker. Finally, the survey assessed vaccine hesitancy through the following question: "Imagine that a vaccine against COVID-19 was available for anyone who wanted it. How likely or unlikely would you be to take the vaccine?" The respondent answer options are "very likely, likely, unlikely and very unlikely". Using this survey measure we are able to classify unvaccinated people according to their willingness to take one, and therefore importantly match people according to vaccine hesitancy.

3. Matching

Table 1 shows that prior to matching our treatment (vaccinated) and control group (not vaccinated) are dissimilar on a variety of variables that are predictive of vaccine status and also potentially mental health. To ensure balance between our treatment and a control group we implement a variety of matching approaches. The covariates we selected for our matching models include age and a dummy variable indicating whether an individual is defined as clinically vulnerable as these variables are the strongest predictors of whether individuals would have been offered a vaccine at the time these surveys were carried out and these variables may also be

[4] Wave 7 began late January 2021 and wave 8 began in March 2021.

[5] More information on the characteristics of individuals belonging to this group is contained here https://www.nhs.uk/conditions/coronavirus-covid-19/people-at-higher-risk/whos-at-higher-risk-from-coronavirus).

Table 1
Descriptive statistics.

Variable	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	*p*-value for *t*-test
	Did not get Vaccine			Did get Vaccine (either one or both)			
GHQ-12	12,423	23.14	6.15	9,562	24.04	5.64	0.00
Age	12,423	49.19	15.64	9,562	61.67	13.84	0.00
Born in UK	12,423	0.87	0.34	9,562	0.90	0.30	0.00
Clinically vulnerable Dummy	12,423	0.34	0.47	9,562	0.56	0.50	0.00
Male	12,423	0.42	0.49	9,562	0.41	0.49	0.20
Key worker	12,423	0.25	0.43	9,562	0.25	0.43	0.62
Couple	12,423	0.69	0.46	9,562	0.73	0.44	0.00
Vaccine willingness	12,423	0.91	0.29	9,562	0.95	0.22	0.00

Note: p-value for *t*-test reports whether the mean/proportion of the variables in the two groups are equal.

correlated with mental health. To that, we add a variable which indicates how responsive individuals are to receiving a vaccine and whether they were classified as a key worker. We also include a regional identifier as there was some regional heterogeneity in the distribution of vaccines and a wave dummy. Finally, we include some socio-demographic characteristics such as gender, relationship status (whether respondents have a partner or not) and whether they were born in the U.K. The results were qualitatively similar whether we included or excluded these sociodemographic variables.

Our first matching approach is known as covariate matching and this approach simply looks to match individuals based on the similarity of their covariates. In practice, it is impractical to match directly on covariates because of the curse of dimensionality and so typically with covariate matching, distance measures like the Mahalanobis distance are employed to calculate the similarity of two individuals in terms of their covariate values and the matching, in turn, is done on these distances (Zhao 2004). With this approach, non-treated and treated groups become only randomly different based on covariates so that the outcomes of the matched non-treated and treated groups, which keep the originally observed values, are comparable under the matched covariate condition.

In addition to covariate matching, we also employ propensity score matching. With this approach we estimate a propensity score for each individual in the dataset using a logit model where a dummy variable capturing whether individuals have been vaccinated is our outcome variable. These estimates are presented in Table A2 in the online appendix.[6] The propensity score is the probability of treatment assignment (i.e. being assigned a vaccine) conditional on observed baseline covariates (Rosenbaum and Rubin 1983). It is a balancing score which means that conditional on the propensity score, the distribution of characteristics across treated and untreated subjects should be similar (see Austin 2011b for further discussion on this point). What this means in practice is that, similarly to covariate matching, once we match individuals on the basis of their estimated propensity score, the distribution of observed baseline characteristics (our covariates) should be the same across our treated units (those who have received a vaccine) and our control units (those who have not received a vaccine).

Once we have a propensity score for each individual, the next step is to match sets of treated and untreated individuals. There are a plethora of techniques that are available to the researcher when conducting this process and there is as yet no clear guidelines available as to which one should be most preferred (e.g. see Baser 2006 for a discussion of this issue). The same is true when it comes to which distance metrics to employ in order to facilitate matching on covariates. Our response was not only test how sensitive our results were to different matching techniques (i.e. covariate versus propensity score matching) but also to test how sensitive our results are to different distance metrics and matching algorithms. The specific matching techniques we applied were the following: *Nearest Neighbour, Mahalanobis-distance, Radius and Kernel*. The first two can be seen as covariate matching based on an estimated distance metric and the last two as propensity score matching based on an estimated propensity score.

With nearest neighbour, we simply match each individual in the treatment group (hereafter referred to as treated unit) with an individual in the control group (hereafter referred to as control unit) based on the closest distance between their estimated Mahalanobis-distance metric (defined later) *with* replacement. Matching with replacement keeps bias low at the cost of larger variance. Bias is lower when employing matching with, as opposed to without replacement, as it means particularly suited control units can be used more than once (with replacement) as matches for treated units. Such a strategy in turn ensures a better balance between our treatment and control group as we are not forcing a match between our treated unit and what could be a dissimilar control unit. Next we employed Mahalanobis-distance kernel matching where matching is based on a distance metric that measures the proximity between observations in a vector of explanatory variables (X) where the distance matrix (MD) is defined as $MD(X_i, X_j) = \sqrt{(X_i - X_j)' \Sigma^{-1} (X_i - X_j)}$ where Σ is the covariance matrix of X.[7]

Thirdly, we employed radius matching which is a type of propensity score matching approach. With radius matching, each treated unit is matched only with a control unit whose propensity score falls in a predefined range of the propensity score of the treated unit. Here we adopt a predetermined calliper (bandwidth) of 0.2*standard deviation of estimated propensity score (see Austin 2011a for

[6] We also report p-value for the balancing test with regard to the propensity score (p-value is 0.091) implying that the matching procedure implemented by kernel matching is balanced. In Figure A1, we also show that after matching, the density of the estimated propensity score is remarkably similar for the treated and the control group.

[7] We use Epanechnikov kernel with an automatic data dependent bandwidth.

further details relating to the choice of appropriate bandwidth). Our second propensity score matching approach was kernel matching with Epanechnikov kernel and data dependant automatic bandwidth selection.[8] This weighting ensures that closer matches gets more weight in the matching process and has the advantage of allowing more flexibility in the accepted matches.

While covariate and propensity score matching are the two most common matching techniques, entropy balancing is another approach that has emerged quite recently as an alternative (see Hainmueller 2012). Entropy balancing is a data preprocessing procedure that looks to directly incorporate covariate balance in the estimation by reweighting a dataset. The preprocessing is based on a maximum entropy reweighting scheme that assigns weights to each unit such that the covariate distributions in the reweighted data satisfy a set of moment conditions specified by the researcher. The covariate balance is directly built into the weight function that is used to adjust the control units and we use exact balance on the first-order moments (mean) of the covariate distributions in the treatment and the reweighted control group.[9] All estimated standard errors are bootstrapped with 100 replications.

4. Matching results

Our main results are presented in Table 2. In columns 1–5, we present our matching estimates using the different matching approaches described above. Looking first at column 1, we can see that the estimated mental health benefit for this sample from being treated (receiving the vaccine) comes to 0.938 ($p < 0.01$) units in our GHQ measure when using nearest neighbour matching. In column 2, we can see that we obtain similar estimates when using Mahalanobis distance matching as the estimated treatment effect for the treated is 0.810 ($p < 0.01$). In columns 3 and 4 we can see that both our propensity score matching approaches, namely radius and kernel predict similar treatment effects (0.94 & 1.07, $p < 0.01$). Finally, we observe that the estimated treatment effect with entropy balancing comes to 1.811 ($p < 0.05$). In sum, our matching estimates suggests that for this group of vaccinated adults, the impact of vaccination is positive with the estimated impact ranging between a 0.8 and 1.8 unit increase in mental well-being as captured by the GHQ. Most of the estimates however converge between 0.8 and 1 units with the estimates when using entropy matching somewhat of an outlier. We adopt a conservative approach in what follows by focusing our attention on the estimates obtained using the other matching approaches.

Irrespective of which matching approach is most preferred, a pertinent question is how large are these estimated effects? That is, all the estimates are statistically significant but does vaccination generate a substantive improvement in mental health and if so how substantive? As a way to illustrate these impacts we can compare these estimated effect sizes with the estimated impacts of other major life events in the wider 'economics of happiness' literature. Fortunately, as the GHQ is a widely used outcome measure, there are a wide array of studies quantifying the impact of various life events for mental health as captured by this outcome variable. An estimated mental health gain of between 0.8 to 1 units in our GHQ measure would, for example, be approximately one half to two thirds of the estimated disutility associated with unemployment (see Howley and Knight 2021; Flint et al., 2013). Unemployment alongside disability are perhaps the two factors noted in the 'economics of happiness' literature as having the most substantive and long-lasting negative impacts for mental health. Other commonly identified negative correlates include divorce and widowhood and our estimates would suggest that the estimated benefit of vaccination for our treated group far exceeds the estimated negative mental health impacts associated with either of these life events. Clearly then for this group of vaccinated individuals, our estimates would suggest that vaccination led to a substantive as well as statistically significant improvement in mental health.

It is important to note that these estimates relate to the treatment group which in our case is just under half of the sample population. This half of the population are also those most likely to be at health risk from Covid-19 given that distribution of the vaccine was based on risk of hospitalisation and death. Earlier we posited that the vaccine will be beneficial for mental health as it will reduce health related anxiety. If this holds true then we would expect that the estimated impact of vaccination to be greater for those most at risk from hospitalisation and death. As a way to test this hypothesis, we divided our sample of treated individuals into sub-groups based on age and the presence of underlying health conditions. These results can also be seen in Table 2. With age, we simply divided our sample into two groups, namely those above and below the median age in our survey which is 56. Understandably the estimates are less precisely estimated but we can see that the mental health benefits associated with vaccination is largely concentrated on the group who are 56 and over. When looking at those under the age of 56 the estimated impacts are comparatively small and not statistically significant across most matching estimates.[10] In a similar vein, we can also see that the mental health benefits are much more pronounced for those with underlying health conditions.

As a final check we estimated the mental health benefit for those who were both 56 and over and clinically vulnerable and compared the estimated impact of vaccination for this cohort to respondents who were both under 56 and not classified as clinically vulnerable. These estimates can be seen in the last two rows in Table 2. What is perhaps most notable here is that when looking at the sub-group of individuals who are both under the age of 56 and not classified as clinically vulnerable, none of the estimates were

[8] Bandwidth is estimated to be equal to 0.0107 by cross-validation with respect to the mean of the propensity score.

[9] If we use both mean and variance of all the covariates to be balanced, the results reported in Table 2 remains qualitatively unchanged.

[10] During the 1st two waves, respondents belonging to the younger age groups and vaccinated were more likely to be key-workers. For example, 37 percent of those who were vaccinated and under the age of 56 were key workers which compares to 20 percent of those who were not vaccinated. To see if having a higher proportion of key workers in our treatment group had any influence on our results, we simply split the younger age cohort (less than median age) into two groups, namely key workers and non-key workers. We observed no meaningful difference, i.e. the estimated mental health impact of vaccination is similar for both groups. These results are presented in Table A3 in the appendix. We are thankful to an anonymous referee for raising this point.

Table 2
Impact of vaccination on mental wellbeing (either one or both doses).

	Covariate matching (Distance Metric)		*Propensity Score*		*Entropy*
	Nearest Neighbour	Mahalanobis-distance kernel matching	*Radius*	*Kernel*	
Whole sample, $N = 21{,}985$	0.938*** (0.322)	0.810*** (0.213)	0.941*** (0.267)	1.075*** (0.401)	1.811** (0.744)
Age equal to or higher than Median age, $N = 11{,}502$	0.821** (0.352)	1.169*** (0.422)	0.792* (0.477)	1.632* (0.831)	3.115*** (0.877)
Age less than Median age, $N = 10{,}483$	0.288 (0.231)	0.386* (0.226)	0.167 (0.188)	0.188 (0.186)	0.079 (0.167)
Clinically Vulnerable, $N = 9{,}644$	1.367*** (0.520)	1.562*** (0.385)	1.516*** (0.450)	1.817*** (0.712)	3.065*** (1.054)
Clinically Not Vulnerable, $N = 12{,}341$	0.370 (0.288)	0.293 (0.199)	0.767*** (0.236)	0.864*** (0.258)	0.250 (0.196)
Clinically Vulnerable and age equal to or higher than median age, $N = 6{,}928$	1.035** (0.516)	2.058*** (0.577)	0.747* (0.432)	1.699* (0.944)	3.720*** (0.663)
Clinically Not Vulnerable and age lower than median age, $N = 7{,}767$	0.168 (0.258)	0.256 (0.256)	0.241 (0.219)	0.195 (0.228)	0.133 (0.206)

Note: Standard errors are calculated using 100 bootstraps. We present the results for Average treatment effect on treated (ATET).
*** denotes significance at 1%,.
** denotes significance at 5%,.
* denotes significance at 10% level.

statistically significant. Overall, we can see therefore that at the population level, the estimated mental health benefits from vaccination are substantive and match if not exceed that of many major life events, but these estimated impacts are heavily concentrated on those who are deemed at significant health risk, namely older and/or clinically vulnerable sub-groups.

5. Robustness checks

In the analysis reported in Table 2 we estimated the mental health benefit associated with receiving either one or two vaccine doses. An important issue highlighted by one of our reviewers is that at the time these surveys were carried out, a much higher proportion of comparatively older individuals had received two vaccine doses. If there is a significant increase in mental health attributable to two vaccine doses relative to one, then this could partly explain the differences across age cohorts we observe in Table 2. A priori, we would argue that there are good grounds to suggest that this is unlikely to be a substantive factor, as at the time these surveys were undertaken, one vaccine was held up as being remarkable effective. In addition, a comparatively small number of individuals had received two vaccines at the time these surveys were carried out.

To examine if this is an issue, in Table 3 we report the results from a robustness check where we broke the vaccinated treated group into two groups, namely those who received either one or two vaccine doses and compared the mental health of both these groups to unvaccinated individuals. We can see in row 1 and 2 of Table 3 below that while our estimates pertaining to those who received two vaccines are rather imprecisely estimated in that they attract large standard errors due to the small numbers of individuals involved, the estimated mental health benefit from vaccination appears qualitatively similar whether we focus on people who have had one vaccine or those who have had two. The results in this table also appear broadly in line with those reported in Table 2. In row 3, instead of comparing vaccinated to unvaccinated individuals, we instead compare individuals who have received two vaccine doses to those who have received one. Here there is little evidence to suggest that having a second vaccine relative to one led to a further improvement in mental health.

In the results presented in Table 2 (and above), we relied on two waves of data, namely wave 7 and 8. An advantage of this approach is that it leaves us with broadly equal numbers of vaccinated and unvaccinated individuals maximizing the chance of obtaining suitable matches. An alternative approach is to rely on three waves of data. This approach increases our sample size but now means that the majority (just under two thirds) of respondents are treated (received a vaccine). This does in turn affect the precision with which we can examine sub-group differences as for example the vast majority of older demographics have been vaccinated when relying on three waves of data. Furthermore, the vast majority ($> 90\%$) of respondents to the survey in wave 9 were vaccinated. This means if using three waves of data (7,8 and 9) we would be largely matching wave 9 treated units to wave 7 and 8 control units and notwithstanding the inclusion of a wide array of matching variables, this does increase the possibility that unmeasured confounding variables may be present.

In response to a reviewer query, in a sensitivity check we did however simply calculate the estimated mental health benefit for this sample as a whole from being treated (receiving the vaccine) but this time relying on three waves of data. We also looked at differences across our age cohorts. These results can be seen in Table A4 in the appendix. Overall we can see in Table A4 that the main population level estimates pertaining to the impact of vaccination for the treated also suggest, similarly to Table 2, significant gains in mental health due to vaccination. Furthermore, while the estimates pertaining to mental health benefits are larger when using 3 waves, we still by and large also observe much larger estimated impacts for older groups.

Table 3
Impact of vaccination on mental wellbeing.

	Covariate Matching (Distance Metric)		*Propensity Score*		*Entropy*
	Comparing both doses with zero[a]				
	Nearest Neighbour	Mahalanobis-distance kernel matching	*Radius*	*Kernel*	
Sample ($N = 12{,}809$)	2.065*** (0.682)	1.381*** (0.506)	0.579 (0.534)	2.971* (1.713)	1.664** (0.758)
	Comparing single dose with zero[a]				
Sample ($N = 21{,}599$)	0.911*** (0.241)	0.792*** (0.180)	0.957*** (0.274)	1.050*** (0.345)	1.813** (0.740)
	Comparing both doses with single [a]				
Sample ($N = 9{,}562$)	0.156 (0.486)	0.496 (0.350)	0.056 (0.336)	0.103 (0.388)	0.068 (0.313)

Note:.
[a] Of the total sample of 12,809 respondents, 386 got 2 doses, of the total sample of 21,599 respondents, 9173 got 1 dose and for the sample of 9562 respondents, 386 of these got 2 doses. Standard errors are calculated using 100 bootstraps. We present the results for Average treatment effect on treated (ATET).
*** denotes significance at 1%,.
** denotes significance at 5%,.
* denotes significance at 10% level.

6. Conclusion

The objective of this study was to estimate the benefits of being vaccinated for Covid-19 for mental health. One potential problem with estimating the impact of vaccination is that vaccines were not distributed randomly. We sought to minimise this potential source of bias by employing a range of matching techniques. With matching, we look to ensure that the distribution of characteristics across treated (have taken a vaccine) and control units are equivalent so that we can more reasonably infer that any differences in mental well-being between them is due to vaccination. Given the unique features of the survey at our disposal we are able to match individuals both when it comes to their probability of being offered a vaccine as well as their level of vaccine hesitancy. While this does not completely eliminate all sources of bias, coupled with the consistency of our estimates across a wide array of matching approaches, it does point towards the robustness of our results.

There is an extensive literature developing concerned with estimating the burden of lockdowns and other social restrictions for mental health. This study can be seen as an initial first step in quantifying the mental health impact of the other major weapon used by governments to protect public health, namely investment in the development of vaccines. By focusing on the impact of vaccination, our estimates can also be seen as capturing the impact of health related anxiety for people's well-being. Our intuition is that given the success of Covid-19 vaccines when it comes to reducing the risk of hospitalisation and death, health related anxiety should we suggest be largely eliminated once vaccinated. As such, our estimates can be seen as lower bound estimates of the psychological distress associated with people's concern for their health during the pandemic.

We find that the mental health benefit from vaccination is significant. Apart from being statistically significant, the estimated gain in mental health is substantive and in keeping with major life events. This, in turn, would suggest that prior to vaccination, general anxiety about becoming ill with covid-19 was a significant and substantive source of psychological distress for many people. We also find that the estimated mental health benefits associated with vaccination appear to be significantly larger for respondents with underlying health conditions (clinically vulnerable) and older demographics.

It is perhaps notable here that young adults are the group most likely not to seek vaccination. In England for example, which has had a successful vaccination drive overall with the vast majority of the population having received at least two doses, vaccination has stalled in recent times, particularly amongst younger cohorts. While undoubtedly a factor, vaccine hesitancy does not seem to be the main driving force as estimates by the Office for National Statistics suggest that less than 10% of 16–29 year olds report that they are hesitant about getting vaccinated (ONS 2021). As we have shown, younger cohorts appear to benefit much less than other groups (e.g. older and/or clinically vulnerable sub-groups) in terms of their own mental well-being from vaccination. In addition to a lack of perceived benefit, vaccination may also be seen by this group as a net cost due to known side effects however small the probability of acquiring these side effects are, or due to worries about the long term consequences of vaccination. Additionally, there are time and effort costs (however small) associated with getting vaccinated. Therefore, for this group, this decision to not get vaccinated could at least partly be simply due to a rational evaluation of the costs and perceived benefits of vaccination, as opposed to vaccine hesitancy per se.

Finally, we conclude by noting that while we have estimated significant benefits of vaccination for mental health, these benefits are not fixed and could vary as people's confidence in vaccine effectiveness changes such as for example through the emergence of new more resistant variants or indeed other treatment alternatives which make the need for vaccination less important. A good avenue for future work therefore would be to track over time the mental health effects of vaccination as that could in turn help us gain a better understanding of the decisions people make when it comes to vaccination.

Declaration of Competing Interest

None to declare.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.euroecorev.2022.104293.

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